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

Internet Appendix

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1 Survey External Comparisons

1.1 Home Market Values vs. Zillow

As a first external quality check on our survey responses, we examine survey question (12.3) that asks respondents: "How much do you think your home would sell for on today's market?" We compare respondents' answers with Zillow home value "Zestimates" from the month of the survey. Figure A1 presents a scatterplot comparing stated home value beliefs against Zillow Zestimates, as well as the 45 degree line. While a number of homeowners seem to place a higher value on their homes than Zillow, there is generally good agreement between the two figures, with a correlation of 0.89.

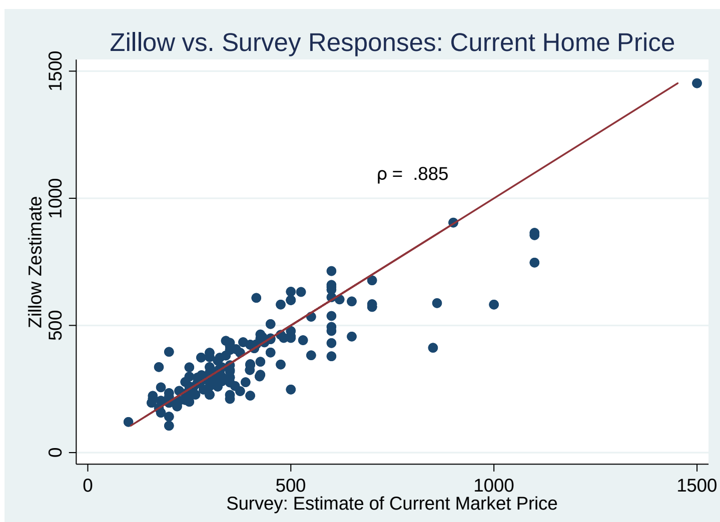

Figure A1. Note: Figure displays the correlation between survey respondents' estimates of their home's current market price (x-axis) versus Zillow Zestimates of their home values from the month of the survey (y-axis).

1.2 Home Purchase Year

Another survey question that can be externally verified is home purchase year. To this end we work to infer purchase dates from publicly available tax assessor records. One complication is that these records include non-arms length sale deeds which are often listed or made at a price of $0, such as quit claim deeds that transfer property into a trust or transfer interest among family members (e.g., after the passing of one of the owners). While some towns provide the history of ownership *names* associated with all past deeds and thus enable us to differentiate deeds within families and identify the genuine purchase date of a home, they mostly do not. We thus chiefly restrict this comparison to homes where the most recent deed on record is clearly as sale to new owners at a positive price.[1] Figure A2 displays the relationship between survey stated and tax assessor-inferred home purchase dates, along with the 45 degree line. With one exception, respondents generally answer this question accurately. The correlation between stated and official purchase year excluding the outlier is 0.996. The one outlier appears to most likely have been a misunderstanding as the respondent's other answers appear sensible. Importantly, we note that this home is located inside the high risk flood zone and that the respondent stated *high* flood risk worry (8/10) and a high perceived flood risk probability. Consequently, excluding this observation from our final sample on account of data quality concerns would only *strengthen* our finding that flood zone inhabitants exhibit lower flood risk worry.

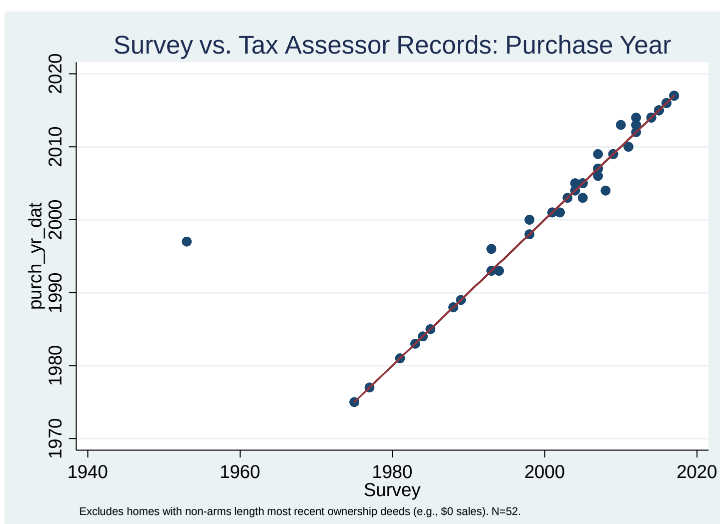

Figure A2. Note: Figure displays survey respondents' stated year of home purchase (x-axis) versus year of purchase from tax assessor records (y-axis).

[1] We also exclude one property where the most recent sale was for $20.

1.3 Respondent Demographics

Table A1 compares key demographic variables in our sample of survey respondents (re-weighted to account for oversampling of coastal homes) against averages of the relevant population values across Bristol, Kent, and Newport Counties in Rhode Island. Data were obtained from the American Community Survey (2015-19, U.S. Census) and from the Consumer Financial Protection Bureau via the Home Mortgage Disclosure Act (2001-17). Our respondents compare reasonably well to population measures, but skew somewhat older and more educated. One notable difference is that our survey focused on single-family homes, whereas population data include multi-family units as well, suggesting that some differences should be expected. Importantly for our purposes, however, we fail to detect a significant association between these demographic measures and sorting into flood zones.

Table A1: Respondent Demographics

Variable	Survey	Cross-County Average
Household Income (Avg.)	$113k	$107k
Age (Median)	51	45
Non-White (%)	13.8%	8.2%
Hispanic (%)	2.8%	4.6%
Education: College+	66%	54%
Number of bedrooms (Avg.)	2.8	2.6
Household Size (Avg.)	2.98	2.32
Non-primary residence (%)	11.45	11.88

2 Further Survey Results

2.1 Sea Wall Expectations

One may be concerned that low flood risk worry among flood zone residents is driven by a belief in future public protective infrastructure investments. Our survey followed up the question eliciting *future* flood risk change expectations with the question "Why do you think flood risk will change this way?" Only *four* respondents mention sea walls or construction as a reason why they expect flood risk to decrease in the future. Our results are not driven by these four respondents; we can easily exclude them and find the same main results, such as that average flood risk worry is significantly lower among flood zone residents, as shown in Table A2 below. One possible caveat is that we did not ask the follow-up question of households who stated that they believe flood risk will remain unchanged in the future. As an additional robustness check, we thus also exclude all respondents who expect future flood risk to remain unchanged from the sample, and again find the same main result of differential flood risk worry across the flood zone, further adding evidence that this result is not driven by heterogeneous future mitigation beliefs.

Table A2: Sea Wall Expectations and Heterogeneous Flood Worry

Sample	Variable	Non-Flood Zone	Flood Zone	Difference (SE)
Full (n=185)	Flood Worry Index (1-10)	5.62	3.61	2.00*** (0.46)
Exclude respondents expecting sea walls to be built (n=181)	Flood Worry Index (1-10)	5.64	3.63	2.01*** (0.47)
Exclude respondents expecting future flood risk to remain unchanged and those expecting sea walls (n=142)	Flood Worry Index (1-10)	5.73	3.97	1.76*** (0.54)

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

2.2 Flood Risk Mitigation

Table A3 reports results from the survey's question about private flood risk mitigation ("Have you taken any precautionary steps to reduce your risk of flooding? [E.g.: install water pump, elevate water heater, etc.] If yes, what steps have you taken?"). This question was only included in the second survey wave and only asked of coastal residents, limiting the sample size. The results, shown in Table A3, are nonetheless reassuring. First, "optimists" list the same number of mitigation measures on average (1.18) as "realists" (1.20). Second and similarly, respondents indicating the lowest level of worry about flooding (1 or 2 out of 10) actually list slightly *fewer* mitigation measures (1.04) on average compared to other coastal residents (1.35). Of course a simple count of mitigation measures ignores the fact that some efforts (e.g., sea wall) provide much greater protection than others (e.g., sand bags). Third, we thus compare flood worry levels between those who report having a sea wall, stilts, and/or have undertaken general elevation.[2] Here we find that respondents listing these significant protection efforts appear, if anything, *more* worried on average (although not significantly so), consistent with the notion that worry drives risk reducing behaviors. In sum, we thus fail to detect evidence that low levels of worry and flood risk optimism are driven by higher levels of private mitigation.

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

Table A3: Flood Risk Mitigation Measures

	Mean	Std. Dev.	Min	Max	N.
Count	1.19	1.14	0	4	47
Mean	Optimists	Realists	Diff.		
Count:	1.18	1.20	0.02		
			(0.35)		
	Not Worried	Worried	Diff.		
Mean	(Worry ≤ 2)	(Worry > 2)			
Count:	1.04	1.35	0.31		
			(0.33)		
Mean	Wall or Elevate	No Wall			
Worry:	4	3.33	-0.67		
			(0.93)		

2.3 Secondary Homeownership

We construct a measure of second homeownership based on property tax records. In particular, property information generally includes the name and *mailing address* of the owners, which may differ from the property's *physical address* if it is a secondary home. Based on this measure we find that only around 15% of homes in our sample are secondary. Adjusting for coastal over-sampling, this implies a population estimate of 11.45% secondary homes. We note that this figure matches external data very well. For example, Home Mortgage Disclosure Act loan origination data for the purchase of homes in the three counties in our study area (Bristol, Kent, Newport) for 2007-2017 indicate that 11.88% are non-owner-occupied primary residences.[3]

In order to gauge the potential influence of those observations, we re-compute the relevant survey results excluding all observations from secondary homes. Reassuringly, we find virtually identical results. Figure A3 presents the analog of Figure 1 in the paper with second homes excluded. The mean worry levels are correspondingly unchanged: Inside the flood zone, 5.62 with and 5.60 without secondary homes; outside the flood zone, 3.65 with and 3.70 without secondary homes, respectively.[4] These results strongly indicate that secondary homeownership is not driving the results.

[3] The data were obtained from URL [www.consumerfinance.gov/] (accessed June 2020).

[4] The means are similar even *among* the second home owners: mean flood concern is 5.8 outside and 3.34 inside the flood zone, respectively.

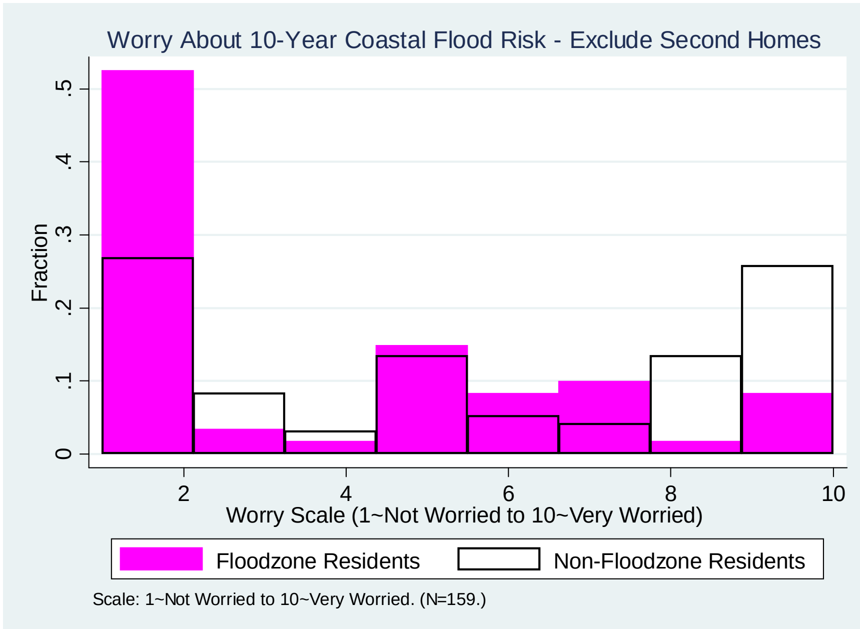

Figure A3. Note: Figure displays distribution of worry about the risk of a coastal flood in the next 10 years with second homes excluded from the sample. Flood zone resident responses are displayed in purple and non-flood zone residents are displayed in white.

2.4 Perceived vs. Inundation Model Flood Risk

First, Table A4 presents results from a linear regression of coastal survey respondents' perceived 10-year flood risk on inundation model-based estimates of 10-year flood risk to their homes. Since the survey elicits flood risk perceptions in ranges (e.g,. 0.2-0.5%), Column 1 uses the midpoint as perceived flood measure (e.g., 0.35%), Column 2 uses the low point (e.g., 0.2%), and Column 3 uses the high point (e.g., 0.5%). All specifications indicate that perceived flood risk is a highly significant predictor of actual flood risk.

Table A4: Actual vs. Perceived Coastal Flood Risk

Subjective Risk Range:	Mid-point	Low	High
	(1)	(2)	(3)
Inundation Model Risk	0.354***	0.306***	0.401***
	(0.0988)	(0.0837)	(0.114)
Constant	0.0794*	0.0550	0.104*
	(0.0464)	(0.0393)	(0.0537)
Obs.	93	93	93
R-squared	0.123	0.128	0.119

Linear regression of coastal residents' subjective 10-yr flood risk belief against home-specific inundation model estimate. Respondents' answers are recorded in ranges (e.g., 0.5-1%), so col. (1) uses mid-points (e.g., 0.75%), col. (2) uses low (e.g., 0.5%) and col. (3) uses high (e.g., 1%) ends of ranges. Standard errors in parentheses. (*** p<0.01, ** p<0.05, * p<0.1).

Second, Table A5 compares the means of perceived versus inundation model-based flood risk estimates. Regardless of the measure used, we see that perceived flood risk is significantly lower than inundation models suggest.

Table A5: Mean Actual vs. Perceived Coastal Flood Risk

10-Yr Flood Risk	Perceived	Actual	Difference (SE)
Mid-point	0.21	0.37	-0.16
			(0.03)***
Low	0.17	0.37	-0.20
			(0.03)***
High	0.29	0.37	-0.09
			(0.04)**

Table reports results from two-sided t-test of mean difference between coastal residents' perceived and inundation-model based flood risk estimates. Rows differ by whether they use the mid-point, minimum ("low"), or maximum ("high") of respondents' subjective risk ranges. N=93.

2.5 Optimist vs. Realist Demographics

This section provides a further information on optimists versus realists from our survey as per the benchmark definition. This comparison is motivated in part by concerns that optimists may rationally be choosing to hold inaccurate beliefs as may occur under behavioral models such as Brunnermeier and Parker (2005). Older agents and those without children and a bequest motive may face lower costs from adopting an excessively optimistic view of flood risks. First, Table A6 compares the groups' means across (i) flood damage expectations, and (ii) demographics. Importantly, we fail to detect evidence that flood risk optimists are also more optimistic about flood damages or insurance reimbursements. To the contrary, optimists hold significantly *lower* expectations of government assistance in case of a flood event. If flood risk optimists were rationally choosing to be optimistic, this choice should presumably carry over. Demographically, the groups appear similar as well, except that optimists are slightly older on average than realists. In order to delve further into this difference, Figure A4 below presents the distribution of ages across optimists and realists. The distribution of optimists is generally shifted to the right, but, importantly, the main difference between the groups is a higher share of agents in their early 50s versus early 40s, and not by a disproportionate share of senior citizens. We also fail to detect evidence that optimists have smaller households which could have signaled fewer children and lack of a bequest motive.

Table A6: Demographics of Optimists vs. Realists

Mean Differences			
Variable:	Optimists	Realists	Difference (SE)
Flood Damage Expectations (percent of home value)	0.36	0.39	0.03 (0.06)
Government Assistance Expectations (percent of damages)	6.98	16.92	9.94** (3.55)
Insurance Expectations (percent of damages)	59.9	56.5	-3.4 (5.2)
Demographics:			
Race (Mixed or Non-White)	0.20	0.11	-0.09* (0.05)
Household Size	2.99	2.84	-0.14 (0.21)
Education	7.04	6.93	-0.12 (0.31)
Male	0.56	0.58	0.02 (0.07)
Age	54.92	51.14	-3.77* (2.22)
Income	130.83	119.56	-11.27 (9.48)
Political Spectrum (0=D, 1=I, 2=R)	0.76	0.74	-0.02 (0.11)
Home Characteristics:			
Year Built	1955.9	1953.7	-2.17 (4.37)
Number of Rooms	6.19	6.06	-0.13 (0.23)
Property Area (sqft)	10,049	9,517	-532.7 (972.3)

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

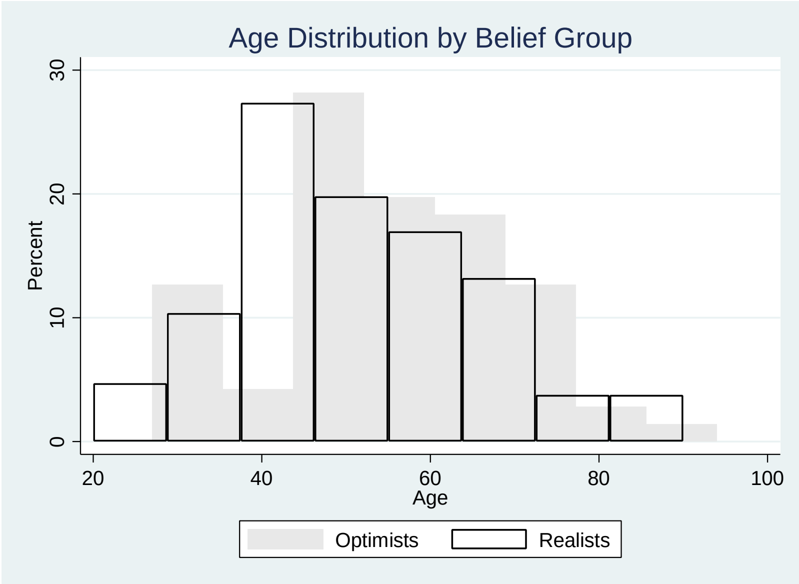

Figure A4. Note: Figure displays the distribution of respondent ages by belief group with optimists in grey and realists in white.

2.6 Flood Experience and Beliefs

Figure A5 showcases the distribution of flood risk worry across agents that have (solid purple) and have not (white) experienced a flood at their homes in the past.

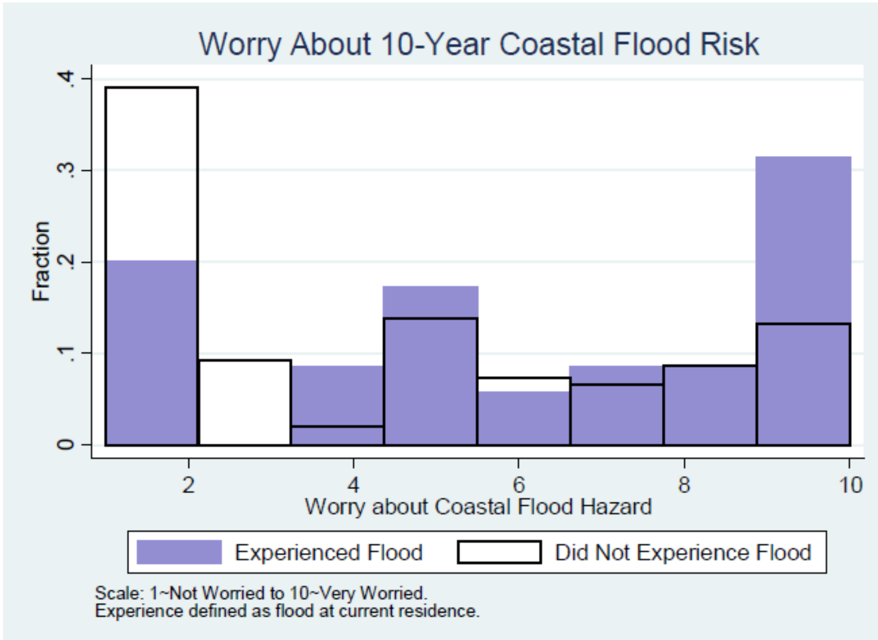

Figure A5. Note: Figure displays the distribution of flood risk worry across respondents that have (solid purple) and have not (white) experienced a flood at their homes in the past.

2.7 Double-Bounded Dichotomous Choice Estimation

Motivation: Based on our theoretical model, the coastal amenity value is a key factor motivating individuals to select a coastal versus non-coastal home. Thus, we require an empirically-grounded estimate of coastal amenity value to calibrate our model. Environmental values, such as the coastal amenity values, can be estimated by various methods (see e.g., Haab and McConnell 2002). One common approach is to use a revealed preference hedonic model to estimate such a value, yet strong correlation between coastal amenities and flood risk has been a long-standing challenge for the hedonic literature (Bin et al. 2008). In addition, our model results highlight that the hedonic approach confounds amenity values, sorting, and future coastal home price expectations, and provide information only on the marginal buyers. For the purposes of our model, we need an unbiased estimate of the coastal amenity value for individuals living on the coast and those who chose to not live on the coast. Thus, while we do estimate the coastal amenity value using a hedonic approach for robustness, we turn to stated preference contingent valuation methods to estimate this important model parameter.

Contingent valuation (CV) has been used for decades to estimate the value of key environmental goods and bads. As a signal of the technique's prominence and important, the National

Oceanic and Atmospheric Administration organized Blue Ribbon Panel composed of top economists including Kenneth Arrow and Robert Solow to generate guidance and best practices for implementation and interpretation of the technique (Arrow et al. 1993). While the technique does have criticisms, especially with respect to estimates of non- or passive-use values such as existence value (Diamond and Hausman 1994), the technique has been well documented as robust to estimate use values, especially when best practices are followed to minimize potential biases (e.g., respondent fatigue, hypothetical bias) (Kling at al. 2012). The original CV technique focused on a single dichotomous choice (yes/no) question that asks individuals about their willingness to pay (accept) for an increase in an environmental good (bad) at a randomly assigned bid price. Later work found that a double-bounded dichotomous choice, asking a first yes/no question, and then following up with a second yes/no question with bid dependent on the first answer, significantly increased the statistical efficiency of the technique (Hanemann et al. 1991).

Estimation: As motivated in the main text and guided by best practices recommendations in Contingent Valuation survey design and implementation (Arrow et al. 1993; Mitchell and Carson 2013) we utilize double-bounded dichotomous choice (DBDC) estimation in order to estimate a plausibly unbiased value of the coastal amenity for both coastal and non-coastal residents. The DBDC question was asked early in the survey to avoid bias due to priming with flood risk information. We utilize two versions of our contingent valuation survey questions, one for current coastal residents and one for current non-coastal residents, to elicit a coastal amenity value for all survey respondents. For non-coastal residents, the following survey question 3.1 asks them about their preferences to move to an identical home within 400 feet of the coast (information inside brackets is for survey interviewers):

> "Imagine that you had the option to instantly move to another house in [current town] that was within 400 feet of the waterfront, but that was otherwise identical to your home: Same house, same school district, same environmental risks, etc. - everything the same except being within 400 feet of the waterfront. Would you be willing to move to such a house if you had to pay $[Bid 1]/month extra in housing costs? Would you be willing to pay: $[Bid 2 depending on yes or no to previous question]/month extra in housing costs?
>
> [Note: If in question, clarify that this is holding flood risk constant.]"

For coastal residents, we asked the same question except for their preferences (i.e., if you could save $[BID 1]/month in housing costs) for moving from their current coastal home to an identical home but 400 feet farther inland. After the first randomly assigned bid, B_i, if the respondent replied "yes", then a second question with a second bid (B_i^u) that is higher than the first ($B_i^u > B_i$) is then asked. If the respondent replied "no", then a second question with a second bid (B_i^d) that is lower than the first bid ($B_i > B_i^d$) is asked. 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.

Based on respondents' answers and DBDC theory (Hanemann et al. 1991), respondents can fall into one of four categories: those who answered yes to the first and second questions ("yy"), those who answered no to both questions ("nn"), those who answered yes to the first and no to the second ("yn") and those who answered no to the first but yes to the second ("ny"). The likelihoods of these outcomes are π^{yy}, π^{nn}, π^{yn}, and π^{ny} respectively. Assuming that individuals are utility maximizing, Hanemann et al. (1991) show that the probabilities can be written as: $\pi^{yy}(B_i, B_i^u) = 1 - G(B_i^u; \theta)$, $\pi^{nn}(B_i, B_i^d) = G(B_i^d; \theta)$, $\pi^{yn}(B_i, B_i^u) = G(B_i^u; \theta) - G(B_i; \theta)$, $\pi^{ny}(B_i, B_i^d) = G(B_i; \theta) - G(B_i^d; \theta)$, where $G(B; \theta)$ is the normal cumulative density function of the individual's true maximum willingness to pay and θ are coefficient parameters. From this, the log-likelihood function has the form: $\ln L^D(\theta) = \sum_{i=1}^{N} \{d_i^{yy} \ln \pi^{yy}(B_i, B_i^u) + d_i^{nn} \ln \pi^{nn}(B_i, B_i^d) + d_i^{yn} \ln \pi^{yn}(B_i, B_i^u) + d_i^{ny} \ln \pi^{ny}(B_i, B_i^d)\}$, where Hanemann et al. (1991) define d_i^{yy}, d_i^{nn}, d_i^{yn}, and d_i^{ny} as indicator variables equal to 1 if the respondents are of that response category and 0 otherwise.

The model is then estimated using maximum likelihood. In addition to the first and second bids, we include the following control variables in the willingness to pay model: the natural log of the estimated home market value, an indicator variable for a respondent being a coastal resident, income, age, number in household, education, race, property size, and number of rooms in the house. Table A7 presents the results of our estimation of coastal amenity values based on the double-bounded dichotomous choice mechanism implemented using the Stata doubleb routine by Lopez-Feldman (2010).

Table A7: 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).

3 Model Output and Extensions

3.1 Future Flood Risk and Amplification Factors

In this subsection, we explain in greater detail our methodology to estimate future flood risk, including our use of amplification factors. We consider two global climate change scenarios following the Representative Concentration Pathways (RCP, van Vuuren et al. 2011). RCP 8.5 is a higher-emissions climate change scenario that is often considered a "business as usual" scenario if society does not make significant reductions to greenhouse gas emissions, with concentrations of carbon dioxide-equivalent atmospheric forcing agents totaling more than 1,200 ppm by the year 2100. This pathway translates to a mean increase in global average temperatures of 3.7 degrees Celsius by the years 2081-2100 relative to the mean value for 1986-2005. We also estimate our model under a global climate policy RCP 4.5 scenario that has carbon dioxide-equivalent emissions peaking by the year 2040 and then declining to have concentrations of carbon dioxide-equivalent agents be less than 600ppm by the year 2100. This translates to a mean likely increase in average global temperature of 1.8 degrees Celsius between the climate averages from years 1986-2005 and 2081-2100 (IPCC 2014).[5]

After establishing a future climate scenario, we then use probabilistic sea level rise projections for Newport, RI based on Kopp et al. (2014). Kopp et al. (2014) is widely used for sea level rise estimates including by the National Oceanic and Atmospheric Administration as well as the Environmental Protection Agency. For example, Kopp et al. (2014) estimate median increases of 20 cm by 2030 and 38 cm by 2050, relative to year 2000 sea levels, in Newport, RI. Buchanan et al. (2017) map these sea level rise projections into corresponding increases in flood risk.

Specifically, Buchanan et al. (2017) define the flood frequency Amplification Factor (AF) as the multiplicative change in the expected frequency of flood events (i.e., water height exceedances) due to sea level rise. For example, if a location is expected to receive one flood event to a given height per year in 2000 and has an AF of 10 for the year 2050, then the expected number of excceedances of that water height in the year 2050 would be 10 ($= 1 * 10$).[6] More formally, letting $N(z)$ denote the expected annual number of exceedences of flood height z, and letting $N(z-\delta)$ the expected number of exceedances of this flood level with sea level rise, Buchanan et al. (2017) define the flood frequency amplification factor AF as:

$$AF(z) = \frac{N(z-\delta)}{N(z)} \sim \frac{\text{Expected exceedances with SLR}}{\text{Expected exceedances without SLR}} \tag{1}$$

Our analysis focuses on water height levels z associated with 100-year floods in the absence of sea level rise. Three further technical notes are as follows.[7] First, the results in Buchanan et

[5] It is yet unclear which, if any, of the RCPs is most probable over the coming century and we do not imply that RCP 8.5 is the most likely future scenario. We utilize RCP 8.5 and 4.5 as they are common benchmarks in the literature. We do not consider other RCP scenarios (2.6, 6.0) due to both data limitations and given that, over our model time horizon, the sea level rise projections for these scenarios are almost identical to RCP 4.5 (Kopp et al. 2017).

[6] An expected AF of 10 is not unusually high. Buchanan et al. (2017) find the median 2050 AF across the U.S. to be 40 in their analysis. The AF for Newport, RI is 7.4 by 2050.

[7] We greatly thank DJ Rasmussen and Michael Oppenheimer for highlighting some of the following issues.

al. (2017) pertain to the exceedance probabilities of water heights at tidal gauges near coastal communities. In locations with large-scale protective coastal infrastructure, such as New Orleans, high water levels need not translate into flood events. We therefore omit New Orleans and other locations with similar concerns (e.g., Seattle) from our analysis. We also omit cities where the nearest tidal gauge featured in Buchanan et al. (2017) is not near the relevant population center (e.g., Miami). Second, our model takes the annual exceedance *probability* as input rather than the frequency of flood events per year. As our model assumes a binomial flood event distribution so that each year can only have one flood or zero, the change in the expected number of annual flood events represents the proportional change in the probability of flooding. This is in slight contrast to the commonly assumed Poisson arrival process, where the exceedance probability F would be related to the expected number of events N via $F = 1 - e^{-N}$ (Hunter 2012). For small probabilities, the two approaches yield similar values. Finally, we note that Buchanan et al. (2017) only provide AFs for the years 2050 and 2100 (relative to a base year of 2000). Our analysis also requires AFs for the model base year 2017 (to reflect sea level rise that has already occurred) and AFs for 2030. To do so, we estimate an exponential interpolation of the expected flood frequency *increase* $(AF_{j,t} - 1)$ in each location j :[8]

$$E[AF_{j,t} - 1] = \beta_{1,j} SLR_{j,t}^{\beta_{2,j}} \tag{2}$$

We estimate the natural logarithm of (2) for each city using as "data" expected AF estimates from Buchanan et al. (2017) for 2050 and 2100 under emissions scenarios RCP 4.5 and 8.5 along with corresponding median sea level rise projections from Kopp et al. (2014). We note that, as our dependent variable is already the *expected* value of flood frequency increases, there is no need to take the expectation again (and thus no need for further adjustments based on Jensen's inequality). We also note that we use as dependent variable the expected flood frequency increase *increase* $(AF_{j,t} - 1)$ since, by definition, $AF(SLR = 0) = 1$. Finally, we use the estimated coefficients to predict flood frequency amplification factors for 2030 based on Kopp et al. (2014) projections for the relevant emissions scenarios and probability scenarios, and based on NOAA data on year 2017 sea level rise.[9]

3.2 Robustness

This section assesses the sensitivity of our main results in the benchmark setting. We first present quantitative robustness results, and then describe some qualitative model extensions below. Un-

[8] We also explored a quadratic approximation but found the exponential to provide a better fit.

[9] NOAA Tides and Currents, URL (accessed July 2020) for Newport, RI: [https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?stnid=8452660\]

less otherwise stated, we change one parameter at a time without adjusting other model elements.

Optimist Share: We begin with the estimated share of flood risk optimists. Uncertainty over this parameter arises both because of potential measurement error in our survey and the possibility of alternate definitions of optimists. Figure A6 displays the estimated initial coastal home price overvaluation as a function of the optimist share. While the overvaluation increases in the optimist share, the sensitivity is quantitatively modest once the share of optimists exceeds the share of coastal homes (14.51%). For example, the benchmark analysis defines "optimists" as those under-estimating coastal flood risk by at least 50% (relative to FEMA flood maps), yielding an estimated population share of 35% and an overvaluation of 13%. Defining optimists more strictly as those under-estimating flood risk by at least 70% would imply a population share of 20%, yielding an overvaluation estimate of 12%. Defining optimists more loosely to imply a 70% population share yields an only modestly higher overvaluation of 16%.

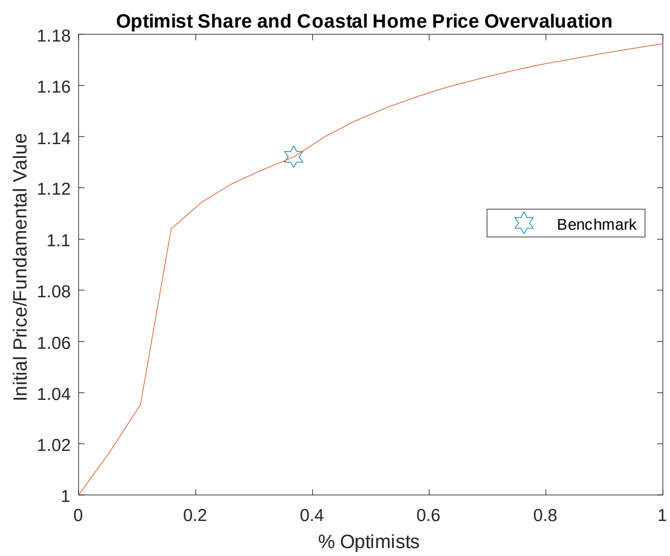

Figure A6. Note: Figure displays the ratio of the initial home price divided by fundamental value (y-axis) as the percentage of optimists varies from 0 to 100% (x-axis).

Coastal Amenity Values: Next, our benchmark analysis uses stated preference methods to quantify coastal amenity values. Uncertainty over these values arises both due to measurement error and alternate methodologies to elicit these values. In particular, hedonic regression can provide revealed preference estimates, but typically cannot cleanly disentangle the different components entering the observed coastal home price premium, as shown in our model results. For comparison, we nonetheless collect housing price and requisite covariate data to generate a hedonic coastal amenity premium estimate, which is around +23% implying an average marginal amenity value of $3.9k per year. Figure A7 showcases results for a range of coastal amenity values including the hedonic estimate, although we again caution that this average marginal hedonic value is not directly comparable to the maximum coastal amenity from the survey. In any event, however, the projected overvaluation does not appear very sensitive to this model input.

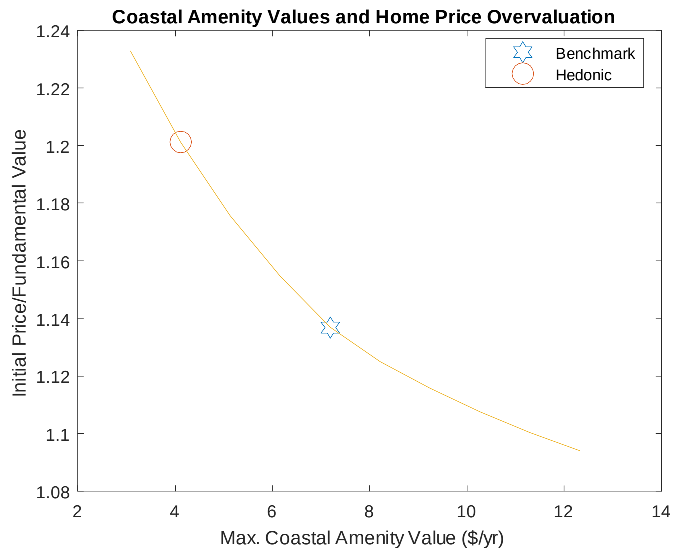

Figure A7. Note: Figure displays the ratio of the initial home price divided by fundamental value (y-axis) as the maximum coastal amenity value (in $1000s/year; x-axis) is varied.

Sea Level Rise Uncertainty and Flood Damages: The next source of uncertainty we confront is over sea level rise. While our analysis already accounts for uncertainty over SLR realizations, it assumes that the relevant distribution is known. One potential concern is that long-run SLR is subject to deep uncertainty particularly over contributions from polar ice sheets, and may thus not be well captured by a single probability distribution (Jevrejeva et al. 2019; Kopp et al. 2017). Importantly, however, for our near- to medium-run focus, the representation of uncertainty through a probability distribution is arguably reasonable. For example, in exploring deep uncertainty over polar ice sheets, Kopp et al. (2017) find that introducing relevant representations of ice sheet dynamics has only limited effects on SLR projection ranges through mid-century. Consequently, in a recent review of uncertainty over sea level rise, Jevrejeva et al. (2019) explicitly note that practitioners such as coastal adaptation planners may want to be "employing probability distributions for the time period of good agreement (through about 2050)" but account for ambiguity over such distributions for longer-run considerations. In addition, even studies that do formally account for deep uncertainty find its effects to be quantitatively limited over our time horizon of interest. For example, Barnett, Brock, and Hansen (2020) consider deep uncertainty in a general climate-economic model, and find that the ambiguity-adjusted probability densities used by the planner do not start to diverge notably from the baseline density until 50 or more years into the future, for both uncertainty over the climate sensitivity (i.e., the equilibrium amount of warming due to doubling of carbon dioxide concentrations) and a climate damage parameter in the benchmark model. Similarly, Lemoine and Traeger (2016) find altogether small effects of ambiguity over climate tipping points. While these considerations motivate our benchmark approach, here we nonetheless consider sensitivity to alternative SLR forecasts. Figure A8(a) displays the projected initial overvaluation for a range of expected flood risk amplification values based on the 5-95% interval identified by Buchanan et al. (2017). The results suggest that initial overvaluation is convex and increasing in expected flood risk amplification. One notable implication of this finding is that our approach of running the model at the expected flood risk amplification factor may thus underestimate the expected overvaluation.

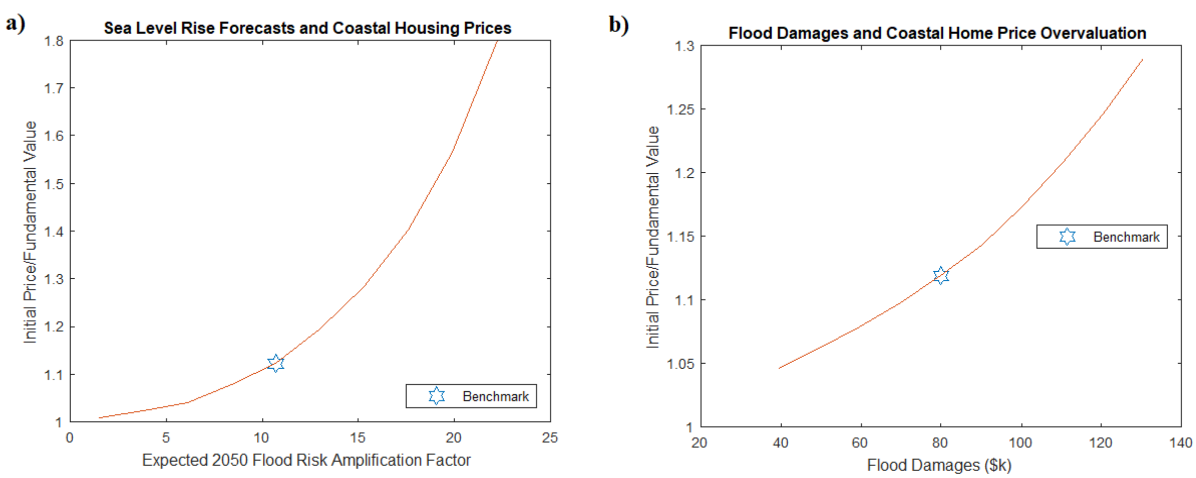

Figure A8. Note: Figure displays the ratio of the initial home price divided by fundamental value (y-axis) when varying the expected 2050 flood risk amplification factor (panel (a)) and flood damages (panel (b)).

Our final continuous sensitivity check varies the assumed level of flood damages in case of a flood event, as shown in Figure A8(b). Not surprisingly, mispricing is increasing in flood damages. The shape of the relationship again appears convex. The estimate also remains economically significant even for lower damage amounts.

Further Robustness: We next consider a number of discrete model changes. Results are presented in Table A9. The first is a behavioral modification that allows optimists to overreact to flood events or the lack thereof. This extension is motivated by empirical studies that have found home prices and flood insurance demand to revert to baseline within only 5-10 years after flood events (Bin and Landry 2013; Gallagher 2014), a pace not matched by a rational Bayesian framework. We thus introduce an overreaction parameter that increases (decreases) the agents' posterior by 15% in case of a (no) flood event to better match empirical studies (see Appendix Section 3.6). 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 A9. Next we consider alternative assumptions about optimists' expectations of long-run flood policy (insurance rates). In the benchmark, optimists assume flood policy will reflect the population-weighted average of beliefs ($\omega^o = \theta^o$). Table A8 shows results for two polar alternative cases, namely that long run rates will reflect only optimists' ($\omega^o = 1$) or only realists' ($\omega^o = 0$) views. The results indicate long-run flood insurance policy changes can significantly affect coastal housing prices in the present. Expectations of long-run availability of cheap insurance leads to an estimated overvaluation of 33%. In contrast, if optimists expect to be forced to pay official risk rates eventually, overvaluation is significantly mitigated (2.5%). The latter assumption is arguably not in line with empirical evidence on limited flood risk capitalization and the responses of housing prices to flood events and flood insurance requirements (e.g,. Gibson and Mullins, 2017), however.

Next we consider a global climate policy scenario consistent with the RCP 4.5 warming scenario (van Vuuren et al. 2011). This emissions scenario is projected to reduce the 2050 flood risk amplification factor in our benchmark area from 11.5 to 7.4 (Buchanan et al. 2017). Our interpolation moreover suggests that flood risk increases by 2030 would be reduced from a factor of 4.79 to a factor of 1.44. As shown in Table A9, with this level of climate mitigation, the projected overvaluation falls to 6.3%. Another alternate policy scenario we consider is one with earlier flood insurance reform, which yields similar results on overvaluation, but significantly lower welfare costs, albeit at a cost of higher price volatility. The next two rows consider alternative flood realization scenarios. These do not affect the coastal home price overvaluation, as both the initial price and fundamental value depend only on *expectations* over flood events. The volatility of prices does, however, depend on storm realizations, as they determine accumulated learning by the time policy reform is enacted. The last two rows of Table A9 consider different values for the prior optimists are assumed to place on the probability that sea level rise forecasts are correct. Doubling or even tripling our benchmark value of 10% yields only slightly smaller estimated values for the initial overvaluation of coastal homes.

Table A8: Further Sensitivity Analysis		
Scenario	Overvaluation	Var($\%\Delta P$)
Benchmark	13%	22
Bayesian updating overreaction (15%)	13%	29
Long-run policy optimism $\omega^o = 1$	33%	103
Long-run policy realism $\omega^o = 0$	2.5%	0.4
Global climate policy RCP 4.5†	6.3%	8.4
Earlier policy reform $T = 2035$	13%	26
Flood events: none	13%	38
Flood events: double (2033 and 2037)	13%	12
Optimists' prior $q^o_{T_1} = 0.2$	12%	16
Optimists' prior $q^o_{T_1} = 0.3$	10%	12

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

Model Misspecification: We note that the robustness analysis presented here is all generated from within our model. In reality, our analysis is of course further subject to potential model misspecification. Important advancements in the literature have recently developed frameworks that can account for this concern in basic climate-economic models (Rudik 2020), including alongside ambiguity and general uncertainty (e.g., Barnett, Brock, and Hansen 2020; see also Brock and Hansen 2018, and further references cited therein). Importantly for our purposes, however, several studies have found that deep uncertainty and model misspecification have limited quantitative effects especially over our time horizon of interest. For example, Rudik (2020) finds that insurance against model misspecification increases the optimal carbon price by only 1-2%. Given these results and the high level of complexity that the integration of a robust control approach into our heterogeneous beliefs housing market model would require,[10] we leave this source of uncertainty for future study.

3.3 Extended Calibration

We first describe details of our extended calibration exercise. We being by connecting our survey data on optimist shares at the county level to the Yale Program on Climate Change Commu-

[10] To our knowledge, robust control models with heterogeneous belief agents also remain rare especially of the form relevant in our setting. Frick (2019) considers a robust monetary policy authority which faces uncertainty over the economy's share of rational versus non-rational agents. However, this framework features only first-order belief heterogeneity as even rational agents do not account for non-rational households' belief process. Anderson et al. (2009) investigate the effects of uncertainty on excess asset returns in a model where agents solve a robust control problem. While professional forecasters' heterogeneous beliefs are used to measure uncertainty, the agents solving the problem are not themselves heterogeneous. Another example, Hansen and Sargent (2012) show that a Ramsey planner may have (endogenously) disparate beliefs from agents under different types of ambiguity.

nications data (YPCCC, Howe et al. 2015). As noted in the main text, the Yale data cannot be used as a substitute to demonstrate the results of this study but instead can complement it. This is because first, the smallest geographic unit in the Yale data is the county or city. Consequently, one cannot compare risk perceptions inside and outside high risk flood zones, or among coastal vs. non-coastal households. Second, the Yale study does not elicit flood risk beliefs, but rather general levels of climate change concern or belief. Third, we require information on counterfactual beliefs of households about flood risk at homes they did *not* purchase, no such data is available in the Yale study or any other surveys products we are aware of. Finally, our analysis requires a joint assessment of households' amenity valuations of coastal living and their risk beliefs, as well as information on potentially confounding beliefs such as about flood damages and government assistance in case of a flood. Again, no such information is available in the Yale survey or comparable surveys we are aware of.

Next, we regress our county-level flood risk optimist shares on the Yale county-level shares that "are not very/not at all worried about global warming". The results, shown in Table A9, imply a predicted flood risk optimist share $\widehat{\theta^o} = -.8 + 3.2(\%$ not worried about global warming). We use this result along with YPCCC estimates for other counties to calibrate the share of flood risk optimists in areas beyond our survey area.

Table A9: Survey Extrapolation

	(1)
% Not worried	3.191**
	(0.053)
Constant	-0.801**
	(0.020)
Observations	3
Adj. R^2	0.999

Reports results of linear regression of our survey-based estimate of the shares of flood risk optimists in each of Kent, Newport, and Bristol Counties, on the Yale survey-based estimate of the fraction not worried about global warming. Standard errors in parentheses. (*** p<0.01, ** p<0.05, * p<0.1).

The remainder of the calibration proceeds as follows. We calculate the share of coastal homes k_1 using the same criterion (within 400 feet of the waterfront) and NOAA Continually Updated Shoreline Product coastline data. Flood risk amplification under sea level rise for each location is quantified based Buchanan et al. (2017) and Kopp et al. (2017) as described in the main paper.[11] In order to quantify the coastal amenity value distribution, we first infer the approximate marginal coastal amenity value by applying our empirical hedonic estimate (23%) to each location's median home price, obtained from Zillow.[12] We then assume the maximum of the distribution Ξ based on the maximum-marginal ratio as in our benchmark calibration (2.6). Finally, to quantify expected flood damages δ, we adopt the benchmark value for damages relative to home price (20%) and compute values based on local median coastal home prices. All other parameters remain at benchmark values.

Climate Policy: Table A10 showcases the sensitivity of our Extended Calibration results to a global climate policy scenario (RCP 4.5).

Table A10: Extended Calibration: Results

	Inputs								Results
Area	Coastal homes k_1 (%)	Optimists θ^o (%)	Max. Amenity Ξ ($k/yr)	E[Flood Risk AF] 2030	E[Flood Risk AF] 2050	e^h	Dam. δ ($k)	P_0 ($k)	Overvaluation$_0$
Benchmark, RI	0.145	0.35	7.7	1.44	7.40	17.3	82	410	6%
Boston, MA	0.023	0.16	13.2	3.36	30.1	39.2	133	664	37%
Wilmington, NC†	0.066	0.48	5.1	3.67	52.8	22.2	51	256	84%
Corpus Christi, TX††	0.046	0.38	3.7	2.02	35.5	12.5	37	187	42%
Tampa, FL$^\flat$	0.109	0.44	4.6	1.05	3.1	7.80	47	234	3%
Charleston, SC	0.035	0.48	8.7	2.02	23	16.7	79	358	28%

Table displays model inputs and results for different cities in a global climate policy (RCP 4.5) scenario. †Optimist share based on New Hanover county Yale survey results and our survey correspondence. Flood risk and sea level rise based on tidal gauges in ††Rockport, TX and $^\flat$St. Petersburg, FL.

3.4 Transaction Costs

This section illustrates the potential effects of adding transaction costs in home purchasing to our framework. We show that, while transaction costs may affect price levels and transition

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

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

dynamics in intuitive ways, importantly for our purposes, they do not affect the overvaluation arising from flood risk misperceptions. In order to generate clear analytic insights, we consider a simplified 3-period version of the model. Period 0 is the present, with initial flood risk level π^L. Period 1 is the medium-term future, where sea level rise will take place and flood risk increases to level π^H. We abstract from ex-ante uncertainty about sea level rise. Realists immediately adjust their beliefs, whereas optimists' are skeptical, so that $\pi_1^o < \pi_1^r = \pi^H$. Finally, Period 2 is the policy reform period where flood insurance at official rates π_2^* becomes mandatory, and *effective* beliefs thus converge. Thereafter, the market is in a steady-state.

We take both initial price levels in coastal P_0 and non-coastal homes P_0^{NC}, and the initial distribution of agents across home types as given. Our illustration focuses on the empirically relevant case where both optimists and realists are initially in the coastal housing market. We are interested in the model's prediction for prices in Period 1, after flood risk increases and as beliefs diverge.

Consider first an initially non-coastal optimist homeowner. The benchmark model predicts that some measure of these agents would move into coastal housing in Period 1 and purchase homes from initially coastal realists. Assume now that buying a home involves transaction cost c. An initially non-coastal optimist would nonetheless want to move to the coast in Period 1 if:

$$-c - P_1 + \beta(\varepsilon^h + \xi^i - \pi_1^o\delta + E_1^o[P_2]) \geq -P_1^{NC} + \beta(\varepsilon^h + E_1^o[P_2^{NC}] \tag{3}$$

Condition (3) can be used to infer the threshold coastal amenity value for optimists who do move to the coast in Period 1:$e^h \equiv \varepsilon^h - (\varepsilon^r - w)$

$$\overline{\xi_1^o} = [c + (P_1 - P_1^{NC}) + \beta\pi_1^o\delta + \beta(E_1^o[P_2^{NC}] - E_1^o[P_2])]\frac{1}{\beta} \tag{4}$$

We see that, ceteris paribus, higher transaction costs c increase the equilibrium marginal buyer's amenity value. This is because higher transaction costs imply that only optimists with sufficiently high coastal amenity values will find it worthwhile to move to the coast. We next consider initially coastal realists who would potentially be interested in selling their homes in Period 1 and moving inland. Using analogous logic to the above, it is easy to show that the equilibrium coastal marginal realist in Period 1 will have threshold amenity value defined by:

$$\beta\overline{\xi_1^r} = [-c + (P_1 - P_1^{NC}) + \pi_1^r\delta + \beta(E_1^r[P_2^{NC}) - E_1^r[P_2])]\frac{1}{\beta} \tag{5}$$

Here we see that the marginal coastal realist's threshold is decreasing in c, ceteris paribus. Intuitively, higher transaction costs deter more realists from selling their coastal homes, thus depressing the marginal remaining agent's amenity value.

We next consider the coastal housing price in Period 1 by solving analytically for P_1. We first note that, analogous to the benchmark model at time $T-1$, agents' Period 1 expectations of coastal home prices after policy reform are given by:

$$\begin{aligned} E_1^r[P_2] &= -c + \frac{\beta(e^h + \Xi(1-k_1))}{(1-\beta)} + \frac{\beta E_1^r[\pi_2^*]\delta}{(1-\beta)} \\ E_1^o[P_2] &= -c + \frac{\beta(e^h + \Xi(1-k_1))}{(1-\beta)} + \frac{\beta E_1^o[\pi_2^*]\delta}{(1-\beta)} \end{aligned} \tag{6}$$

In the benchmark model, we further assumed that realists correctly anticipate actuarially fair policy reform $E_1^r[\pi_2^*] = \pi^H$, whereas, for optimists $E_1^o[\pi_2^*] \leq \pi^H$. The precise values and assumptions are not important for demonstrating the effects of transaction costs, however. Next, note that the non-coastal housing price is constant and pinned down by the rental market. That is, for agents who are initially renters to be indifferent between renting and buying a non-coastal home, it must be the case that:

$$\beta(\varepsilon^r - w) = -c - P_t^{NC} + \beta(\varepsilon^h + E_t[P_{t+1}^{NC}])$$

Once again defining $e^h \equiv \varepsilon^h - (\varepsilon^r - w)$, we thus obtain the dynamic non-coastal home pricing condition $P_t^{NC} = -c + \beta(e^h + E_t[P_{t+1}^{NC}])$ implying the steady-state value:

$$P^{NC} = \frac{-c + \beta e^h}{1-\beta} \tag{7}$$

The last condition we need to solve for prices is the housing market clearing condition for coastal homes:

$$\frac{\theta^o}{\Xi}(\Xi - \overline{\xi^o}_t) + \frac{(1-\theta^o)}{\Xi}(\Xi - \overline{\xi^r}_t) = k_1 \tag{8}$$

Finally, combining (4)-(8) we can solve for coastal housing prices in terms of model primitives:

$$P_1 = \beta(\Xi(1-k_1) + e^h - [(1-\theta^o)\pi_1^r + \theta^o\pi_1^o]\delta - \beta[(1-\theta^o)E_1^r[\pi_2^*] + \theta^o E_1^o[\pi_2^*]]\delta - c + \frac{\beta(e^h + \Xi(1-k_1))}{(1-\beta)}) \tag{9}$$

Coastal housing prices are consequently a function of coastal and general housing amenity values, population-weighted average expectations of current and future flood risks, transaction costs, and long-run future home values. Importantly for our purposes, (9) demonstrates that coastal home prices will exceed fundamentals if the population share of optimists θ^o exceeds zero and if optimists under-estimate current and/or future flood risk. More formally, we can compare (9) to the fundamental coastal home value P_1^* :

$$P_1^* = \beta(\Xi(1-k_1) + e^h - \pi_1^r\delta - \beta E_1^r[\pi_2^*]\delta - c + \frac{\beta(e^h + \Xi(1-k_1))}{(1-\beta)}) \tag{10}$$

Finally, subtracting (10) from (9) showcases that the overvaluation due to flood risk misperceptions does not depend on transaction costs c:

$$P_1 - P_1^* = \theta^o \left[(\pi_1^o - \pi_1^r) + \beta(E_1^o[\pi_2^*] - E_1^r[\pi_2^*])\right] \delta \tag{11}$$

Equation (11) demonstrates that the overvaluation of coastal homes depends only on the population prevalence of optimists and the severity of their flood risk misperceptions.

3.5 Allocative Inefficiency

Figure A9 visualizes the allocative inefficiency that arises due to flood risk optimism in our benchmark setting. It specifically 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).

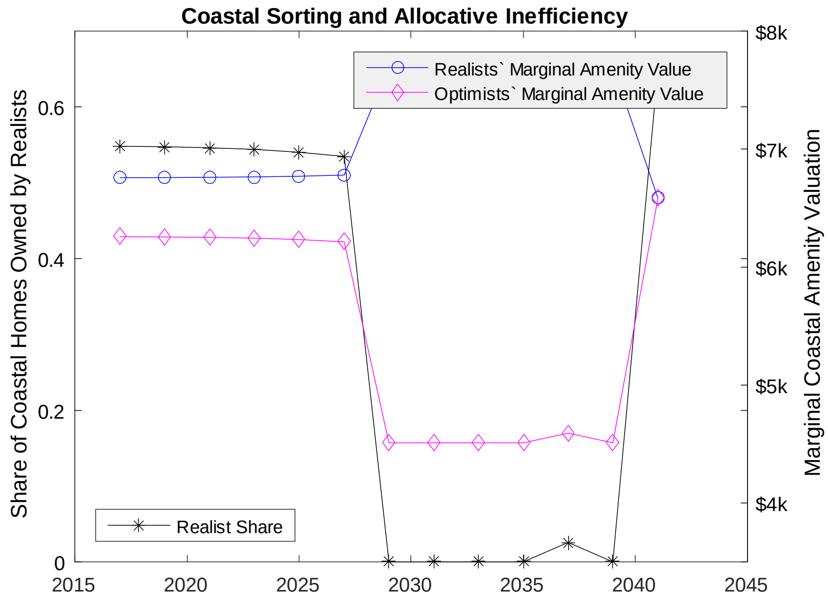

Figure A9. Note: Figure displays the share of coastal homes owned by realists (in black stars) and the marginal coastal optimist's (in pink diamonds) and realist's (in blue circles) respective coastal amenity values over time, evidence of the allocative inefficiency.

In line with the survey results indicating that misallocation is currently limited (paper Figure 5), the model projections imply that misallocation is initially low, that is, that marginal amenity values of optimists and realists differ only modestly at present. As the flood risk increases and beliefs diverge more, however, 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, and with empirical evidence that transaction volumes of vulnerable homes increased after the release of worsening sea level rise projections (Bernstein et al., 2019). In our model, the departing realists are replaced by optimists with lower amenity values (pink line with diamonds). After the storm event assumed to occur in 2037 lowers coastal home prices and thus allows some realists - those with the very highest amenity values - to move back in. Only once the policy reform at time T enforces the internalization of real risk rates do prices adjust so that all realists with appropriate amenity valuations return to coastal housing markets, restoring allocative efficiency.

3.6 Overreaction to Flood Events

While the benchmark model assumes rational Bayesian updating, the sensitivity analysis also considers a behavioral extension to agents overreacting to flood events or the lack thereof. We specifically incorporate an overreaction parameter γ into agents' updating rules as follows (illustrated here for $T_1 \leq t < T$):[13]

$$\begin{aligned} \widetilde{q}^{o}_{t+1}|_{\text{Flood=1}} &= \Pr(\pi^H|_{\text{Flood=1}}) = \frac{(\pi_1 \cdot q^o_t) \cdot (1+\gamma)}{\pi_1 q^o_t + (1-q^o_t)\pi^L} \\ \widetilde{q}^{o}_{t+1}|_{\text{Flood=0}} &= \Pr(\pi^H|_{\text{Flood=0}}) = \frac{((1-\pi_1) \cdot q^o_t) \cdot (1-\gamma)}{(1-\pi_1) q^o_t + (1-q^o_t)(1-\pi^L)} \end{aligned} \tag{12}$$

Several empirical studies have found that home prices and flood insurance demand to revert to baseline within only 5-10 years after flood events (Bin and Landry 2013; Gallagher 2014). Setting $\gamma = .15$ allows our model to match this pace, as shown in Figure A10 below. The figure specifically showcases the evolution of optimists' beliefs in a hypothetical scenario without flood insurance policy reform and with only one flood event in period 2035. With a 15% overreaction, the optimist's beliefs converge back to their pre-flood levels within ten years.

[13] 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 (12) as an analogous modified updating rule to match the empirical evidence.

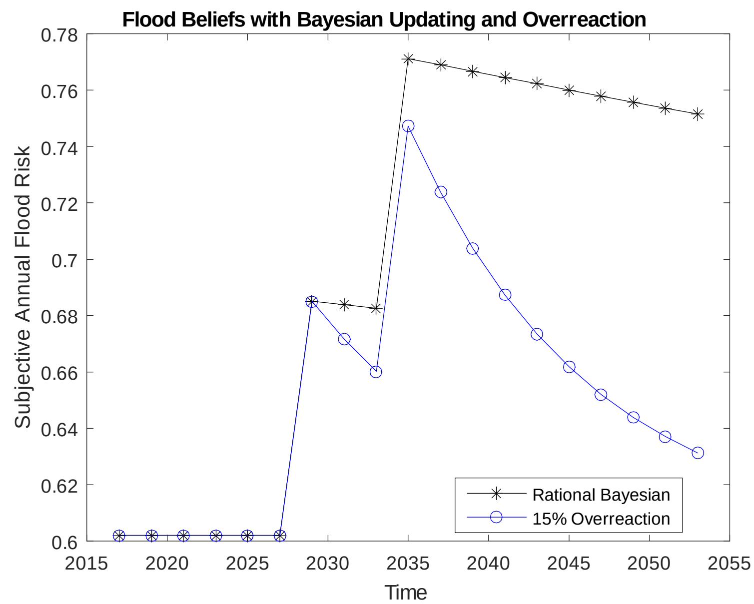

Figure A10. Note: Figure displays the subjective annual flood risk (y-axis) over time based on an assumption of a rational Bayesian learner versus a 15% overreaction a flood event in 2035.

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

The 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:

$$P_0^* = \beta(e^h + \overline{\xi_0^r} - \pi^r\delta + E_0^r[P_1]) = \beta(e^h + \overline{\xi_0^o} - \pi_0^o\delta + E_0^o[P_1]) \tag{13}$$

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:

$$\pi^r > \underbrace{\pi_0^o > \pi_1^{o,NC_{0,1}}}_{\substack{\text{Bayesian}\\ \text{Updating}}} \underbrace{> \pi_1^{o,C_{0,1}}}_{\text{+Rationalization}} \tag{14}$$

Beliefs (14) 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 (14): $E_1^{o,C_{0,1}}[P_2^{m_2}] \geq E_1^{o,NC_{0,1}}[P_2^{m_2}] \geq E_1^r[P_2^{m_2}] \geq E_0^r[P_1^{m_1}]$. 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.[14] The equilibrium coastal home price in period 1 is thus determined by the interaction between these groups. More formally:

$$\begin{aligned} P_1^* &= \underbrace{\beta(e^h + \overline{\xi_1^r} - \pi^r\delta + E_1^r[P_2])}_{\text{Newly marginal coastal realists}} = \underbrace{\beta(e^h + \overline{\xi_1^o} - \pi_1^{o,NC_{0,1}}\delta + E_1^{o,NC_{0,1}}[P_2])}_{\text{Marginal new coastal Bayesians}} \\ &< \underbrace{\beta(e^h + \overline{\xi_0^o} - \pi_1^{o,C_{0,1}}\delta + E_1^{o,C_{0,1}}[P_2])}_{\text{Long-term coastal Bayesians}} \end{aligned} \tag{15}$$

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.

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

Empirically, the key implication of (15) 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 survey responses from all residents leads to an overestimate of optimism compared to the relevant population. 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 - exhibit a similar distribution including flood risk optimism, as shown in Figure A11. While the moving history questions were added to the survey late, thus limiting the sample size underlying Figure A11 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).

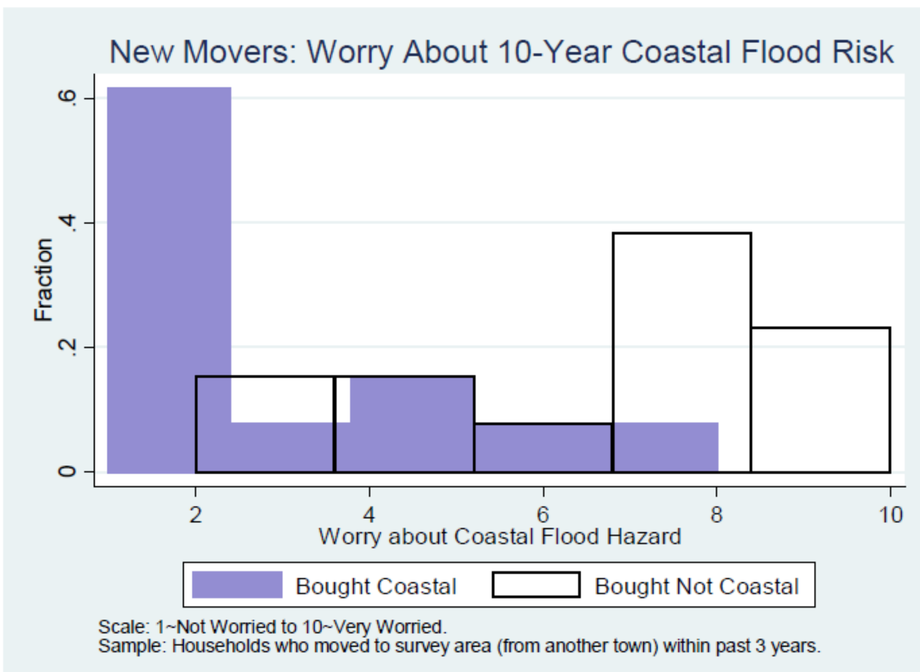

Figure A11. Note: Figure displays the distribution of flood risk optimism for respondents who have moved in the past three years.

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.

4 Hedonic Estimation

This section describes our hedonic estimation of coastal amenity premiums and flood risk capitalization in our empirical setting. 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. Our results are robust to excluding these data. Next, 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 Flood Insurance Reform Act passage (July 6, 2012), the Homeowner Flood Insurance Affordability Act (HFIAA) passage (March 21, 2014) and introduction (Oct. 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 (2010-2017) 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 2010-2017:

$$lnP_{it} = \beta_0 + \gamma_i X_i + \delta c_i + \beta_1 f_i + \beta_2 BW_{it} + \beta_3 f_i * BW_{it} + \alpha_c + \theta_t d_{Yt} + \varepsilon_{it} \tag{16}$$

As shown in Table A11, 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}). Column (1) 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. Column (2) excludes the inland area of North Smithfield from the sample. Column (3) considers warranty deeds only. Finally, Column (5) restricts the sample to the time before the HFIAA was introduced. The results indicate a significant coastal housing premium of around 23%. Given the median coastal home price in the data ($424k), at a real interest rate of 4%, this estimate corresponds to an annual coastal value of $3.9k.

Table A11: Hedonic Home Price Estimation

Dependent Variable: Log(Real Sales Price) ($2015)

	(1)	(2)	(3)	(4)
Land Area (Acres)	0.135***	0.224***	0.152***	0.0951***
	(0.0425)	(0.0598)	(0.0340)	(0.0313)
Age	-0.00407***	-0.00399***	-0.00323***	-0.00433***
	(0.000786)	(0.000879)	(0.000647)	(0.000907)
Age^2	1.48e-05***	1.63e-05***	1.21e-05***	1.55e-05***
	(3.74e-06)	(4.99e-06)	(4.07e-06)	(4.64e-06)
#Bathrooms	0.219***	0.220***	0.235***	0.217***
	(0.0234)	(0.0244)	(0.0195)	(0.0275)
#Bedrooms	-0.000934	3.30e-05	0.0129	0.00379
	(0.0198)	(0.0247)	(0.0195)	(0.0251)
Coastal (w/in 400 feet)	0.242***	0.229***	0.183***	0.264***
	(0.0648)	(0.0614)	(0.0523)	(0.0660)
FEMA Flood zone	-0.0459	-0.0403	-0.0146	-0.0583
	(0.0719)	(0.0746)	(0.0756)	(0.0898)
During Biggert-Waters Act	0.0777	0.0988*	0.0639	0.0671**
	(0.0487)	(0.0530)	(0.0472)	(0.0309)
Flood zone*Biggert-Waters	0.00215	-0.00535	-0.0429	-0.0287
	(0.0707)	(0.0726)	(0.0622)	(0.0611)
Constant	12.33***	12.34***	12.26***	12.24***
	(0.119)	(0.116)	(0.0963)	(0.118)
Observations	2,979	2,502	2,280	1,266
R-squared	0.596	0.614	0.634	0.604
Adj.R-sq.	0.592	0.610	0.629	0.596

Reports results of OLS regression of log(Real Sales Price) on indicated variables plus Census tract- and year fixed effects. Col. (2) excludes North Smithfield. Col. (3) restricts sample to "Warranty" claims. Col. (4) excludes homes after HFIAA introduction.. Standard errors clustered at the census tract level and in parentheses.

The second use of the hedonic analysis is to provide direct empirical evidence on the capitalization of flood risks in our empirical setting, specifically over a longer time horizon (1970-2017). 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 (2019) fail to detect such a decline 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. We analyze these data with 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.[15] We also restrict the specification to "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 $\delta_{i,\tau}$:

$$lnP_{it} = \beta_0 + \alpha_i + \theta_t d_{Yt} + \sum_{\tau=1970-74}^{2010-14} + \beta_3 f_i * \delta_{i,\tau} + \varepsilon_{it} \tag{17}$$

Figure A12 visualizes the estimated hedonic flood zone premium over time. Once again, we fail to detect the pattern predicted by the homogeneous rational beliefs model in our setting, which would indicate that the flood risk premium should become more negative over time as flood risk is increasing.

[15] 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 to be a significant confounder in our setting.

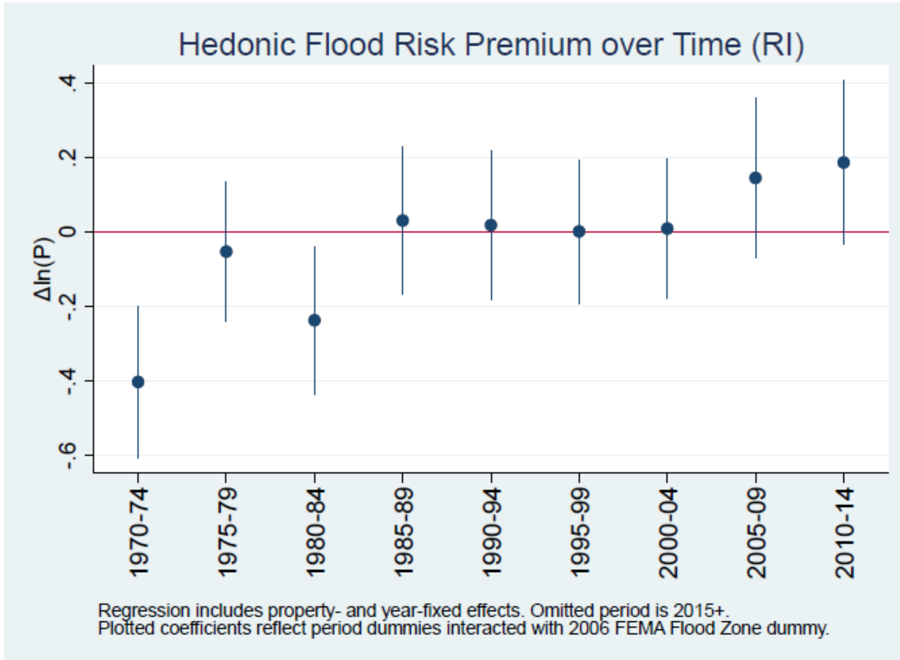

Figure A12. Note: Figure displays the estimated hedonic flood zone premium over time (1970-2017) from transactions in Bristol County, Rhode Island.

Finally, Table A12 shows the estimation results in full detail. 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.

Table A12: 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.

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