Annoyed, but Not Alarmed: Sea Level Rise, Chronic Inundation, and Coastal Housing Markets

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Abstract

Coastal communities are projected to experience 50–100 days of high-tide flooding (HTF) annually by the mid-2040s. While such chronic inundation would pose serious threats to livability, surprisingly little is known about how these risks are priced into coastal housing markets. Leveraging plausibly random variation in HTF occurrences, we find that exposure to HTF depresses both rents and home prices, with the impact on rents being three times larger—suggesting that homebuyers anticipate future recovery in rental values. We show that this optimism likely stems from expectations of future adaptation, particularly by governments.

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1 Introduction

With rising sea levels, coastal communities in the U.S. face a growing threat from high-tide flooding (HTF)—the intermittent inundation of low-lying areas during high tides (Sweet 2018). Projections indicate that by the mid-2040s, the number of HTF days will more than double, reaching 50 to 100 days annually (Thompson et al. 2021). Because HTF seriously impairs mobility and thereby disrupts daily life and economic activity (Lee et al. 2024), such chronic and recurrent exposure will threaten the livability of coastal areas. Yet, surprisingly little is known about how these risks are priced into coastal housing markets.

In this paper, we provide the first empirical evidence on how HTF risk affects coastal housing markets. For this, we leverage variation in HTF occurrences as a source of information shocks that affect individuals' beliefs about HTF risk. This strategy builds on two key insights from the literature: first, individuals use past exposure to similar hazards as a source of information to update their beliefs about future environmental risks (Bin and Landry 2013, Deryugina 2013, Gallagher 2014, Hong et al. 2019, Choi et al. 2020); and second, that while HTF rarely results in direct asset losses, it significantly depresses rental values—consistent with market responses to perceived risk (Lee et al. 2024).

To guide our empirical analysis, we begin with a simple Gordon growth model where housing prices reflect the present value of current and future rental income (Gordon 1962). This framework illustrates how the relative impact of HTF information shock on rents versus housing prices can reveal individuals' expectations about future HTF risk. For example, if a recent increase in HTF days has a larger effect on housing prices than on rents, it suggests that individuals expect rents to continue declining—perhaps because they interpret the flooding as a signal of accelerating sea level rise, in line with scientific projections (Thompson et al. 2021). In contrast, if the impact is greater on rents than on prices, it implies that individuals anticipate a future rebound in rental values, likely because they interpret the shock as either transitory noise or as persistent but manageable through future adaptation.

To take these insights to data, we compile daily water level data from 84 NOAA gauge stations across coastal states in the contiguous US and compare them with the gauge-specific flood thresholds. We then match coastal zip codes to the nearest gauge station to construct a zip code level panel of HTF events. This data is linked with monthly zip code level data on housing prices, rents, and housing inventory. To explore mechanisms, we use survey data on local climate change opinions. For identification, we exploit plausibly random variations in HTF occurrences.

We start our empirical exercise by estimating the impact of subjective beliefs about HTF risk on housing prices, using the number of HTF days in the past 12 months as a source of information shock. Our analysis shows that exposure to one additional HTF day (in the past 12 months) lowers housing price by 0.09% or \$439 at the sample mean home value. We then benchmark this effect against the impact of HTF on rental rates as documented in a companion paper (Lee et al. 2024), and find that only about one-third of the adjustment in rents is reflected in housing prices. Consequently, the price-rent ratio rises by 0.14% for each additional HTF day, suggesting that the housing market anticipates a rebound in future rents.

To assess whether this muted housing price response might be explained by the tendency for prices to adjust more slowly than transaction volumes, we examine HTF impacts on housing inventories (Keys and Mulder 2020). We find that the number of days on market as well as the number of new listings remain largely unchanged, while the number of active listings does not seem to increase, suggesting that the limited price adjustment is unlikely to be driven by reduced transaction activity. We also show that our main findings are robust to a range of alternative specifications—including the use of additional covariates, more granular fixed effects, and different temporal or spatial samples as well as to alternative measures of the information shock, such as lagged HTF exposure over the past 48 months or scientific forecasts of future HTF frequency.

Finally, we investigate the source of market optimism about future rents—specifically, whether it reflects a belief that shock in HTF exposure are temporary and expected to revert to normal levels, or whether it stems from local optimism about future mitigation and resilience efforts. To do this, we test whether the impact of recent HTF exposure on the price-rent ratio is larger in (1) areas with low serial correlation in HTF (i.e., where a shock is more likely to be viewed as transitory), or (2) areas where individuals hold stronger expectations about future adaptation. Our results show that the response of the price-rent ratio does not vary with the degree of serial correlation; instead, the impact is more pronounced in areas where individuals express stronger confidence in future adaptation, indicating that optimism about mitigation efforts underlies the observed market response. Importantly, given that prevalent adaptation approaches to HTF—and sea level rise more generally—often involve

large-scale public investment such as seawalls, these expectations closely reflect beliefs about future government intervention (EPA 2009, IPCC 2022).

Related literature. This paper contributes to two different strands of literature. First, it is related to a large literature studying the impact of various climate risks on the housing market (Hallstrom and Smith 2005, McCoy and Walsh 2018, Gibson and Mullins 2020, Ma et al. 2024). We add to this literature by providing the first evidence on the relationship between housing prices and HTF, a risk that has received relatively little attention despite projections that it will become a defining feature of life in many coastal communities in the near future (Thompson et al. 2021, Logan et al. 2023).

Within this literature, this paper is most closely related to studies on sea level rise (SLR) risk (Bernstein et al. 2019, Baldauf et al. 2020, Murfin and Spiegel 2020, Giglio et al. 2021, Bakkensen and Barrage 2021). Prior work typically models SLR risk as a long-term threat, with impacts projected to materialize around the end of the century (e.g., by 2100). More importantly, it often treats SLR as a binary outcome—either permanent inundation or no inundation—thereby overlooking intermediate-stage risks and behavioral responses that may emerge well before full inundation. In contrast, we focus on HTF—an intermittent form of inundation that is expected to intensify and ultimately lead to permanent inundation. By allowing time-varying information shocks, we allow risk perceptions and adaptation expectations to evolve over time, enabling housing market responses during these intermediate stages. Juxtaposing our findings with previous studies suggests that markets may treat chronic and permanent flood risks as fundamentally different—despite their shared physical origins. This disconnect raises important questions about whether housing markets are accurately internalizing the full trajectory of SLR risk.

Second, and more broadly, this paper extends the existing literature that studies the source of market underreaction regarding climate risk. While earlier works have emphasized the role of imperfect information and/or or behavioral biases (Bin and Landry 2013, Gallagher 2014, Hino and Burke 2021, Bakkensen and Barrage 2021, Gourevitch et al. 2023, Lee 2024), our findings suggest that expectation about future adaptation opportunities, especially government policy intervention could attenuate price adjustment. This resonates with recent works that have documented moral hazard due to the federal government's *existing* disaster policies (Gregory 2017, Kousky et al. 2018, Baylis and Boomhower 2023, Peralta and Scott 2024).

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This paper proceeds as follows. Section 2 introduces conceptual framework to guide our empirical analysis. Section 3 provides background on the HTF, details the data sources, and provides summary statistics. Section 4 analyzes the impact of recent HTF exposure on housing market, while Section 5 explores the mechanism. Section 6 concludes.

2 Conceptual Framework

To understand how information shocks shape housing prices and rents, and what they reveal about individuals' beliefs regarding HTF risk, we consider a simple Gordon model in equation (1) (Gordon 1962). In this framework, housing price P in time t = 0 is determined by the discounted sum of future rental income where rental income is growing at rate g.¹ The capitalization rate, or the implied rate of return, is r - g, where r is the opportunity cost of capital. For owner occupied units, future rental income can be interpreted as utility from flow of housing services.

$$P_0 = \frac{R_1}{r-g} \tag{1}$$

Suppose that there is an information shock at t = 0 that increases the perceived HTF risk. Because HTF disrupts daily life and economic activity, a higher HTF risk will reduce R_1 (Lee et al. 2024). If this shock does not affect g, namely if homebuyers believe that the rent will continue to grow at the same rate, the impact of the information shock on housing prices and rents should be identical.²

Alternatively, if homebuyers interpret the information shock as a signal of increasing risk over time, such as accelerating sea level rise that may lead to permanent inundation at some future time T, it will lower the rent growth rate as well ($\Delta g < 0$). In this case, the impact on the housing price will exceed the impact on rents. Conversely, if homebuyers expect rents to rebound despite an initial decline ($\Delta R_1 < 0$), either because they believe future HTF frequency will decline or anticipate effective adaptation, the rent growth rate will rise ($\Delta g > 0$). Notably, given commonly discussed

 $^{{}^{1}}R_{1}$ is the only rent term used directly in equation (1): R_{t} for t > 1 are incorporated through the constant growth rate g.

²While we interpret market responses to the information shock primarily through changes in g, we remain agnostic about whether the adjustment occurs through expectations of rent growth (g), the discount rate (r), or both. For instance, higher perceived HTF risk could raise r, as heightened systemic volatility or uncertainty increases the required rate of return, or lower g, if rents are expected to grow more slowly—or both. Each of these effects increases r - g and thereby reduces P_0 ; vice versa holds when risk perceptions decline or adaptation is expected.

strategies for mitigating sea level rise risk—such as seawall construction or wetland restoration, the expectations about adaptation are often closely tied to expectations of public investment (IPCC 2022).³

Take theory to data. The key insight from the theoretical discussion is that by comparing the impact of an information shock on current housing prices and rents, we can infer how individuals perceive the persistence of HTF risk. Our primary empirical analogue of the information shock is past HTF exposure. This approach follows a voluminous literature showing that individuals use past exposure to similar hazards as a source of information to update their beliefs about future environmental risks (Bin and Landry 2013, Deryugina 2013, Gallagher 2014, Hong et al. 2019, Choi et al. 2020). While we use the number of HTF days in the past 12 months as our baseline proxy, we demonstrate that our results are robust to alternative choices, including lagged HTF counts over the past 48 months or scientific forecasts of HTF frequency.

One potential concern with interpreting recent HTF exposure as an information shock is that HTF could also cause direct asset losses, confounding the information channel with physical damage effects. Indeed, prior studies have used "near-miss hurricanes" to isolate pure information effects from physical destruction (Hallstrom and Smith 2005). However, as shown by Lee et al. (2024), HTF events rarely cause physical damage to property, which allows us to interpret the observed housing market response to HTF as an information effect—by altering expectations about future HTF risk.

3 Background and Data

3.1 High Tide Flooding

*HTF: measurements and trends.*⁴ HTF—also known as recurrent tidal flooding, sunny day flooding, or nuisance flooding—refers to the temporary inundation of low-lying coastal areas during periods of exceptionally high tides, even in the absence of storms or other severe weather events. To measure the occurrence of HTF at the gauge-day level, we follow the National Oceanic and Atmospheric Administration (NOAA), and define HTF as an event where the daily maximum water level exceed

³For a detailed discussion of these strategies, see IPCC (2022).

⁴Much of the background discussion on HTF in this section closely follows Lee et al. (2024), which provides a more detailed treatment of HTF patterns, definitions, trends, and idenfitication properties.



Figure 3.1: HTF Measurement and its Characteristics. Panel (a) illustrates HTF measurement using Gauge ID 8443970 in 2018. Panel (b) shows the annual number of days with HTF during 2015–21 by region.

the "minor" but remain below the "moderate" flood threshold (Sweet 2018).

To illustrate, Figure 3.1 (a) overlays the 2018 time series of daily maximum water levels from a gauge station in Boston with its site-specific flood thresholds. As shown in the figure, July 15 is an example of a day that experienced HTF. Notably, the highlighted grey area (March 4) illustrates that water levels can exceed the minor flood threshold as either a precursor to or a residual effect of a larger flood event. To avoid misclassifying such instances as HTF (i.e., avoid false positives), we treat days within a \pm 3-day window of a moderate or major flood event as non-HTF, even if water levels exceed the minor threshold. We also separately document dates when water levels exceed the moderate or major thresholds to control for the impact of large floods in our robustness checks.

To measure HTF spatially—that is, to identify areas subject to HTF—we use NOAA's HTF inundation map.⁵ This map delineates areas projected to be inundated when water levels reach the site-specific minor threshold. The mapping uses a "bathtub" approach: any location where land elevation is lower than the modeled water surface is classified as inundated. The water surface is constructed by interpolating across tide gauge stations at the minor flood threshold.

Appendix Figure A.1 illustrates the map for the Mid-Atlantic region. Notably, inundated areas are not limited to locations directly adjacent to the ocean; in some cases, they extend far inland via connected water systems—most notably tidal rivers, such as the Delaware and Hudson Rivers—

⁵Accessed at https://coast.noaa.gov/slrdata/ on July 11, 2022. We use the Flood Frequency product. For further details on mapping methodology, see https://coast.noaa.gov/data/digitalcoast/pdf/slr-high-tide-flooding.pdf.

where tidal influences can propagate well upstream.⁶

It is worth highlighting that the mapping process underscores the similarities between HTF and permanent inundation events. Specifically, the HTF inundation map is produced using the same methodology as NOAA's Sea Level Rise (SLR) inundation map products, which have been widely used in prior studies examining permanent inundation risks (Bernstein et al. 2019, Baldauf et al. 2020, Giglio et al. 2021). Specifically, for both products, inundation is determined by the condition "Inundated = (Land Elevation \leq Water Surface)". For the HTF map, the water surface is defined as mean higher high water (MHHW) plus the site-specific minor flood threshold; for the SLR map, it is MHHW plus the selected (e.g., 2 ft) SLR scenario (NOAA 2017, n.d.).⁷ The key difference is that HTF maps capture intermittent flooding events, while SLR maps represent permanent inundation.

While tidal movement is not a new phenomenon, the frequency of HTF has risen sharply over the past two decades across the contiguous US, primarily due to sea level rise (Sun et al. 2023). Further, this trend is expected to accelerate—by mid-2040, many cities along the Atlantic Coast are projected to experience 50–100 of HTF annually (Thompson et al. 2021).

HTF: impacts and adaptation strategies. Existing anecdotal and scientific evidence suggests that HTF seriously disrupts daily life, primarily by impairing road networks. For instance, individuals experience loss of income (e.g., fewer patron visits to restaurants), loss of leisure (e.g., giving up outdoor exercise at a park), loss of learning (e.g., children have difficulty getting to school), health risks (e.g., delayed ambulance services) or other nuisances (Flechas and Staletovich 2015, Alvarez and Robles 2016, Kensinger 2017, Hino et al. 2019, Mazzei 2019, Hauer et al. 2021, Bittle 2022, Choi-Schagrin and Sanders 2023, Hauer et al. 2023). Despite these disruptions, asset losses from HTF are minimal (Lee et al. 2024).

Given that sea level rise is projected to accelerate throughout much of this century (IPCC 2022), adaptation to HTF is becoming increasingly important. Aerts et al. (2014) classifies adaptation strategies into two broad categories: reducing tidal flooding occurrence through engineering and nature-based protection measures, and reducing exposure by encouraging migration or retreat. In the US, many local governments have already committed to substantial investments in "protection"

⁶Consistent with this, local news outlets have reported instances of tidal flooding in cities such as Philadelphia and Washington, D.C., even though they are not directly located on the open ocean (Muyskens 2023, Wood 2024).

⁷The second document can be accessed at https://coast.noaa.gov/data/digitalcoast/pdf/slr-high-tide-flooding.pdf (accessed on Apr 8, 2025).

infrastructure. For example, the City of Miami Beach has invested over \$400 million in pumps, elevated roads, and seawalls (Flechas and Staletovich 2015), while New York City has announced a citywide resiliency program with an estimated cost of \$20 billion (City of New York 2013). These large-scale infrastructure projects are particularly attractive to property owners, as they help preserving housing values while spreading costs more broadly across taxpayers. In contrast, retreat-based strategies—often implemented through zoning regulations or stricter building codes—can impose significant costs on individual homeowners, especially through reductions in property values, which may partly explain why the protection approach is much more widespread in many urban coastal areas around the world (IPCC 2022).

HTF as a research design. Figure 3.1 (b) shows that even after aggregating 84 gauge stations into three regional groups—thereby removing gauge-specific idiosyncrasies—substantial temporal variation in HTF frequency remains throughout our study period (2015—21). For example, the North Atlantic region experienced only 3 HTF days in 2015 but 11 in 2018. Moreover, these temporal fluctuations differ across regions, introducing an additional source of identifying variation. Appendix Figures A.2 (a) and (b) further demonstrate that, after controlling for year and gauge fixed effects, HTF occurrences exhibit only weak serial correlation, resembling a random draw from an underlying distribution.

These variations are similar in spirit to numerous studies that leverage weather shocks—such as temperature, precipitation, and windstorms, which are often modeled as random spatial realizations and "offer strong identification properties" (Dell et al. 2014). Indeed, variation in HTF occurrence like other weather shocks—is driven by multiple interrelated physical factors, including large-scale atmospheric and oceanic patterns such as the El Niño–Southern Oscillation (ENSO), as well as localized conditions like wind speed, water density, and tidal forces (Sweet 2018).

3.2 Data Description

Coastal flood history. We construct a coastal flood history dataset by comparing NOAA's verified daily high water level data, retrieved using R package "rnoaa", to gauge-specific flood thresholds. Specifically, we use 84 gauge stations in the contiguous US that have flood thresholds from Sweet



Figure 3.2: Map of the Study Area. This figure shows our main sample, which consists of 1,469 zip codes that have non-missing ZHVI and ZORI data over 2015–21 and have an overlap with the NOAA inundation map.

(2018) (See Appendix Figure A.3 for gauge locations).⁸ As detailed in Section 3.1, we compare the time series of daily water levels to gauge-specific flood thresholds and define a binary indicator that equals 1 when the daily water level falls between the minor and moderate flood thresholds. To connect zip codes with HTF events, we match each zip code to the nearest NOAA gauge station.

Housing market. For housing prices and rents, we use the Zillow Home Value Index (ZHVI) and the Zillow Observed Rent Index (ZORI), respectively, at the ZIP code by month level. These are dollar-denominated, constant-quality measures of typical home values and asking rents in a given region.⁹ Because both ZHVI and ZORI are quality-adjusted, the price–rent ratio can be interpreted as reflecting the value of a comparable, representative property (Gupta et al. 2022). This enables a direct comparison of the impact of HTF on housing prices and rents. Juxtaposing ZHVI and ZORI to analyze housing market dynamics has been widely adopted in recent literature (Gupta et al. 2022, Brueckner et al. 2023, Ramani et al. 2024).

To track housing inventory, we use monthly data from Realtor for the same set of zip codes in our main sample over the July 2016, which is the month data starts, to December 2021. Specifically, we focus on new and active listing counts and median days a property is on the market following Gupta

⁸Ad hoc flood thresholds (i.e., minor, moderate, and major) for each gauge are typically set by local stakeholders, such as NOAA Weather Forecast Offices and city emergency managers, based on their local knowledge of the relationship between water levels and flood impacts. Sweet (2018) produces objective and nationally consistent gauge-specific flood thresholds by applying statistical methods to these ad hoc thresholds.

⁹For more detail, see https://www.zillow.com/research/methodology-neural-zhvi-32128/ (accessed March 7, 2023) and https://www.zillow.com/research/methodology-zori-repeat-rent-27092/ (accessed March 2, 2023).

et al. (2022).

Climate opinion. To explore mechanism, we collect county-level climate opinion data from the Yale Climate Opinion Survey. The data documents climate change beliefs, risk perceptions, policy preferences based on national survey data (n > 28,000) gathered by the Yale Program on Climate Change Communication and the George Mason Center for Climate Change Communication (Howe et al. 2015).¹⁰ The survey was conducted in 2014, 2016, 2018–21, and we collapse across different years to leverage county-level cross sectional variations in various climate opinions. While the data asks rich set of questions, we focus on three variables that are pertaining to beliefs about climate change and expectations on adaptation.¹¹ These variables are (1) the share of people who believe that the President should do more to address climate change; (2) the share of respondents who believe that climate change will start to harm people in the US within the next 10 years; and (3) the share who report being worried about climate change.

3.3 Summary Statistics

Table 3.1 shows summary statistics for key variables used in our empirical exercises from our main sample, which consists of 1,469 zip codes within the 22 coastal states in the contiguous US that have both housing price and rental information over the March 2015 to December 2021 period, and an overlap with the NOAA inundation map (see Figure 3.2).¹² Panel A presents summary statistics for housing market variables. A few points are worth noting. First, an average housing price is \$463,772 over the sample period. This is more than twice higher than an average price for all other zip codes in the Zillow housing price dataset that are outside of our main sample (\$216,553). The difference in the housing price (at least partly) reflects a premium for higher amenity of being closer to the ocean. Lee et al. (2024) documents a similar pattern for rental rates as well. We leverage temporal variations in HTF occurrences to control for these time-invariant unobserved characteristics.

Second, the median distance between a zip code *centroid* and a NOAA gauge station is 13.6 miles, indicating that HTF exposure is well-measured for most zip codes. For some zip codes that are af-

 $^{^{10}{\}rm More}$ details can be found at https://climatecommunication.yale.edu/visualizations-data/ycom-us/ (accessed on May 7, 2023).

¹¹Because the survey does not include a direct question about expectations for future adaptation, we construct a proxy measure using these variables. See Section 5.1 for details.

¹²These states are AL, CA, CT, DC, DE, FL, GA, LA, MA, MD, ME, MS, NC, NJ, NY, OR, PA, RI, SC, TX, VA, and WA.

Variables	Min.	Max.	Median	Mean	Std.Dev.	Ν	
Panel A: Housing Market							
Housing Price (CPI Adjusted)	$17,\!977$	$3,\!984,\!326$	$342,\!061$	463,772	$395,\!246$	$119,\!043$	
Annual Rent (CPI Adjusted)	150	$391,\!867$	$18,\!349$	20,384	$12,\!276$	$119,\!043$	
Active Listing Counts	0	$2,\!646$	76	118	145	$95,\!953$	
New Listing Counts	0	540	38	45.7	34.9	$95,\!953$	
Median Days on the Market	1	340	56	58	25.1	$95,\!953$	
Distance between Zip Code and Gauge	0.3	122	13.6	20.9	21.8	$119,\!043$	
Panel B: Flood Exposures							
N High Tide Floods (in Past 12 Months)	0	44	5	5.6	4.9	119,043	
N Larger Floods (in Past 12 Months)	0	11	0	0.48	0.99	$119,\!043$	
Panel C: Climate Change (C.C) Opinions							
Believe Harm in 10 Years from C.C (%)	36.9	64.7	54.6	54.6	5.7	119,043	
Worried about C.C (%)	44.5	78	64.5	64.2	7.1	119,043	
President should Do More on C.C $(\%)$	42.7	71.6	61.4	61.1	5.5	$119,\!043$	

Table 3.1: Summary Statistics for Key Variables

fected by tidal rivers, the distance can be much larger. In Section 4, we show that our findings remain robust even when we restrict the sample to the Northeast, a region with a denser network of gauge stations.

Panel B shows that the number of days with HTF in the past 12 months is an order of magnitude larger than that of moderate or major floods. Also, the difference between the mean (5.6) and median (5) number of days with HTF suggests that the average number of days with HTF is unlikely to be driven by a few extreme values.

4 Effect of High Tide Flooding on the Housing Market

Estimation framework. To estimate the impact of the change in subjective HTF risk on housing

market outcomes, we estimate the regression model in equation (3).¹³

$$\log(Y_{czmt}) = \sum_{k=0}^{11} \beta_k \tilde{f}_{z,t-k} + \alpha_z + \theta_{ct} + \theta_m + \epsilon_{czmt}$$
(2)

under the restriction that $\beta_k = \beta$ for all k. In this case, the model simplifies as: $\sum_{k=0}^{11} \beta_k \tilde{f}_{z,t-k} = \beta \sum_{k=0}^{11} \tilde{f}_{z,t-k} = \beta F_{zmt}$, and thus $\beta = \sum_{k=0}^{11} \beta_k$. As shown in Appendix Figure A.4, the empirical impulse-response patterns are broadly consistent with $\beta_k = \beta$, and thus we use a more parsimonious model.

¹³Note, our main specification implicitly embeds an impulse-response function in which each month's flood exposure has an identical marginal effect on current outcomes. Specifically, if we write $F_{zmt} = \sum_{k=0}^{11} \tilde{f}_{z,t-k}$, where \tilde{f} is the number of HTF days in a given month, then equation (3) can be interpreted as a constrained version of the distributed lag model:

$$log(Y_{czmt}) = \beta F_{zmt} + \alpha_z + \theta_{ct} + \theta_m + \epsilon_{czmt}$$
(3)

Here Y_{czmt} is various outcome variables such as the logged housing price, logged rent, and logged days on the market, for zip code z within county c in month m at year t. The key independent variable is F_{zmt} , the number of days with HTF in the past 12 months for a zip code z at time mt. This is our empirical measure of information shock from Section 2, which subsequently affects perceived HTF risk. We also explore alternative measures of information sources such as scientific forecasts on future HTF frequencies or a longer belief formation window for robustness checks. β captures the impact of being exposed to an additional day of HTF in the past 12 months on Y_{czmt} , which captures the reduced form relationship between information shock and housing outcomes since we do not directly observe beliefs.

We also include a rich set of fixed effects. Zip code fixed effects α_z control for time-invariant zip code level characteristics, which allow us to leverage plausibly random deviations from average HTF exposure for each zip code. We also include year by county (θ_{ct}) and month (θ_m) fixed effects, which accounts for local economic shocks in a given year and seasonality in the housing market and HTF occurrences, respectively.

Our baseline model does not include any further controls than these set of fixed effects because HTF is a plausibly random event that is driven by physical process, which provides strong identification properties (Dell et al. 2014). Nonetheless, we also show that our results are robust to the inclusion of time-varying zip code-level characteristics such as the number of days with moderate or major flood events in the past 12 months, the fraction of population with college degree, the fraction of minority populations, median income, and the fraction of rental units, or to the inclusion of more granular fixed effects.

Results. Table 4.1 shows the impact of the HTF on housing market outcomes. The estimated coefficient in column (1) indicates that being exposed to one additional day of HTF within the past 12 months reduces housing prices by 0.09%, or \$439 at the sample mean housing price. Notably, discussions in Section 2 implies that \$439 is the present value of expected future rental income losses due to belief updating in response to an increase in recent HTF exposure.

In column (2), we reproduce the impact of HTF on rental rates from Lee et al. (2024), estimated

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var.:	$\log(Price)$	$\log(\text{Rent})$	$\log (P/R)$	log (Active Listings)	log (New Listings)	log (DOM)
HTF Days (Past 12 Months)	-0.0009*** (0.0002)	-0.0023^{***} (0.0004)	$\begin{array}{c} 0.0014^{***} \\ (0.0003) \end{array}$	-0.0024 (0.0015)	-0.0004 (0.0013)	0.0003 (0.0008)
Zip Code FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	119,043	$119,\!043$	$119,\!043$	$95,\!943$	$94,\!847$	$95,\!953$

Table 4.1: Effect of High-Tide Flooding on the Housing Market

Note:

This table presents the effect of HTF on the housing market using equation (3) for zip codes overlapping with the NOAA inundation map. Column (2) is reproduced from Lee et al. (2024). Columns (1)-(3) are based on ZHVI and ZORI while columns (4)-(6) are based on data from Realtor.com. All outcome variables are in log scale. Standard errors are clustered at the county level. p < 0.1; p < 0.05; p < 0.01.

using the identical specification and sample as column (1). The estimated coefficients is about three times larger than column (1) at -0.23%, suggesting that current rental price change due to HTF is not fully reflected in the housing price. Consequently, the price-rent ratio in column (3) increases by 0.14% for each additional day with HTF in the past 12 months.

In columns (4)–(6), we examine the impact of HTF on transaction-related variables to test whether the muted housing price responses reflect a lag in price adjustment relative to transaction volumes (Keys and Mulder 2020). While our data do not include sales volume, we use the number of new and active listings and days on the market, which measure housing inventory and market liquidity, respectively (Gupta et al. 2022). In column (4), we find that HTF exposure does not increase the number of active listings (if anything, it reduces the number, which implies a hotter market). While a reduction in active listings could be driven by fewer new listings—potentially indicating a slower market and lower transaction volumes—column (5) rules out that possibility. Similarly, column (6) shows no meaningful impact on the median days on market. Taken together, these results suggest that the muted price response is unlikely to be driven by a meaningful reduction in transaction volume or housing supply.

In Figure 4.1, we estimate the impact of recent HTF exposure using a more flexible specification that allows for potential non-linear effects. To do so, we first residualize the number of HTF days



Figure 4.1: The Impact of HTF on Housing Prices and Rental Rates. These plots show the relationship between the number of HTF days in the past 12 months and (a) log housing prices and (b) log rental rates. Each figure overlays a binned scatter plot with a fitted linear regression line from Table 4.1 columns (1) and (2). All variables are residualized with respect to zip code, month, and county-by-year fixed effects.

in the past 12 months, log prices, and log rents with respect to zip code, month, and county-by-year fixed effects. We then generate binscatter plots for (a) housing prices–HTF and (b) rents–HTF. The estimated points indicate that a linear approximation provides a good fit: when overlaid with the regression lines from Table 4.1 columns (1) and (2), the scatter plots closely align with the fitted lines, suggesting that our results in Table 4.1 are unlikely to be an artifact of linear parameterization in equation (3).

In Table 4.2, we conduct a series of robustness checks. In Panel A, we show results from alternative specifications. In column (1) we find that inclusion of time-varying zip code level characteristics such as the number of days with moderate or major flood events in the past 12 months, the fraction of population with college degree, the fraction of minority populations, median income, and the fraction of rental units does not affect the impact of HTF on price-rent ratio from our preferred specification. This is plausible given that variations in HTF occurrences are plausibly random. In column (2), we control for more granular seasonality. Specifically, we include county by month fixed effects, which can account for local seasonality in housing market or HTF occurrences, and find that the impact on price-rent ratio remains identical.

Columns (3) and (4) test the robustness of our main results using alternative samples. Column (3) estimates equation (3) using data from the 2000–14 period to investigate whether the muted price response observed in our main sample (2015–21) reflects earlier capitalization of HTF risk. Specifically,

	(1)	(2)	(3)	(4)		
Panel A: Alt. Specifications						
Dependent Var.:	$\log (P/R)$	$\log (P/R)$	$\log(\text{Price})$	$\log (P/R)$		
HTF Days (Past 12 Months)	0.0014***	0.0014***	-0.0008**	0.0015***		
	(0.0003)	(0.0003)	(0.0002)	(0.0003)		
Sample	Main	Main	2000-14	Northeast		
Controls	Yes	No	No	No		
Zip Code FE	Yes	Yes	Yes	Yes		
Month FE	Yes	No	Yes	Yes		
Year-County FE	Yes	Yes	Yes	Yes		
Month FE-County FE	No	Yes	No	No		
Observations	$119,\!043$	$119,\!043$	246,777	$75,\!255$		
Panel B: Alt. Information Sources						
Dependent Var.:	$\log(\text{Price})$	$\log (P/R)$	$\log(\text{Price})$	$\log (P/R)$		
HTF Days (Past 12 Months)	-0.0015***	0.0021**				
	(0.0004)	(0.0008)				
HTF Days (Past 13-24 Months)	-0.0012*	0.0013				
	(0.0005)	(0.0012)				
HTF Days (Past 25-36 Months)	-0.0005	0.0014				
- 、 ,	(0.0006)	(0.0013)				
HTF Days (Past 37-48 Months)	-0.0009	0.0005				
- 、 ,	(0.0005)	(0.0009)				
HTF Days (Forecast)	· · · ·	· · · · ·	-0.0008	0.0020		
			(0.0015)	(0.0023)		
Sample	Main	Main	2018 - 21	2018 - 21		
Controls	No	No	No	No		
Zip Code FE	Yes	Yes	Yes	Yes		
Month FE	Yes	Yes	No	No		
Year-County FE	Yes	Yes	Yes	Yes		
Observations	$116,\!597$	$116,\!597$	5,799	5,799		

Table 4.2: Effect of High-Tide Flooding on the Housing Market (Robustness Check)

Note:

This table presents the effect of HTF on the housing market using alternative specifications (Panel A) and information sources (Panel B). In Panel A, we (1) controls for time-varying zip code level characteristics; (2) include more granular County by Month fixed effects; (3) estimate the impact of HTF on housing prices over 2000–14; and (4) repeat Table 4.1 column (1) using zip codes that are in the 11 Northeast states. In Panel B, we allow belief formation based on longer past (columns (1)-(2)) and future forecasts (columns (3)-(4)). Standard errors are clustered at the county level. *p < 0.1; **p < 0.05; ***p < 0.01.

prior studies have highlighted the 2013 release of the IPCC climate assessment report as a pivotal moment in shaping public expectations about sea level rise, which is a critical driver of HTF (Bernstein et al. 2019). If housing markets had already internalized these risks before our study period (2015–21), we would expect a stronger price response during 2000–14. However, we find that the estimated impact of HTF on housing prices during this period is nearly identical, at -0.08%, effectively ruling out this explanation. Note, because ZORI data starts in 2015, we cannot estimate the impact on the price-rent ratio. Column (4) further confirms the robustness of our results by restricting the analysis to the 11 Northeast states, which have a denser network of tide gauge stations and therefore have greater spatial precisions in HTF measurements.¹⁴ The similarity in point estimates suggests that our main findings are not driven by potential measurement error in HTF exposure.

In Panel B, we assess the robustness of our results to alternative measures of the information sources. In columns (1) and (2), we allow individuals to form expectations based on both recent and more distant past experience by including three lags of HTF exposure. Column (1) indicates that the impact of HTF days in the past 12 months on housing prices is slightly larger than in our baseline specification, but, as shown in column (2), the impact on the price-rent ratio is even more pronounced.

Estimates in column (1) also indicates that even if homebuyers form beliefs based on a longer history (e.g., 48 months) than renters (e.g., 12 months), the impact of HTF days in the past 12 months is still larger for rents, which indicates that a smaller impact on prices than rents is unlikely to be driven by systematic differences between homebuyers and renters in how they form expectations about future HTF risk.

In columns (3) and (4), we test an alternative belief formation practice in which homebuyers base their expectations based on scientific forecasts rather than historical HTF exposure. For this, we use NOAA's HTF annual outlook data, available for the years 2018–21.¹⁵ To match this data's annual frequency, we aggregate housing prices accordingly and regress them on the forecasted number of HTF days. Although the coefficient estimate is imprecise due to the limited sample size, the point estimate for housing prices in column (3) is nearly identical to that in our main specification, while the impact on the price-to-rent ratio in column (4) is slightly larger. Taken together, these results

¹⁴These 11 states are CT, DC, DE, MA, MD, ME, NH, NJ, NY, RI, and VA.

¹⁵These reports were retrieved from https://tidesandcurrents.noaa.gov/pub.html#htf (accessed Dec 23, 2024).

indicate that our main findings are robust to alternative representations of the HTF information set, including both extended historical exposure and forward-looking forecasts.

5 Discussion

5.1 Mechanism

Section 2 highlights two key points: (1) the impact of information shock can be larger on rents than housing prices when the market holds optimistic beliefs about future rental income, and (2) such optimism may reflect expectations that HTF frequency will revert to a more typical baseline over time, or that future adaptation efforts will effectively lessen its impact. In Table 5.1, we empirically test these potential mechanisms. To focus on the relative impact on rents vs. prices, we use log of price-rent ratio as outcome variables.

We begin by testing whether a mean-reverting belief is the primary driver of market responses. This type of belief formation is more likely to arise when past events have lower information value (i.e., lower serial correlation). Appendix Figure A.2(c) shows that the year-to-year serial correlation in HTF occurrences varies substantially across gauge stations. Since higher serial correlation implies greater informational value of past events (and lower correlation implies less), we divide the sample into above- and below-median serial correlation groups (in absolute value) and re-estimate equation (3) separately for each.

If this was the main driver of optimism, we would expect a larger coefficient for the low-serial correlation group, where individuals are less likely to revise beliefs in response to recent HTF. However, columns (1) and (2) show that the effect of recent HTF exposure on the price–rent ratio is similar across both groups, providing little support for this mechanism.

Next, we examine whether expectations on future adaptation is the main driver. To proxy for adaptation expectations, we use the share of people who believe that the President should do more to address climate change. This measure is particularly relevant in our context, because, as discussed earlier, effective adaptation to HTF is anticipated to originate largely from governmental action (IPCC 2022). While this variable reflects normative preferences ("should") rather than predictive expectations ("will"), it still serves as a useful proxy because to the extent that elected officials act as delegates of their constituents, public support for climate action is likely to translate into future

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	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var.:	$\log (P/R)$	$\log (P/R)$	$\log (P/R)$	$\log (P/R)$	$\log (P/R)$	$\log (P/R)$
HTF Days (Past 12 Months)	$\begin{array}{c} 0.0014^{***} \\ (0.0004) \end{array}$	$\begin{array}{c} 0.0014^{***} \\ (0.0003) \end{array}$	$\begin{array}{c} 0.0011^{***} \\ (0.0002) \end{array}$	0.0019^{***} (0.0006)	$\begin{array}{c} 0.0012^{***} \\ (0.0004) \end{array}$	$\begin{array}{c} 0.0017^{***} \\ (0.0004) \end{array}$
Sample	Low Serial	High Serial	Low Policy	High Policy	Low Adapt	High Adapt
Zip Code FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-County FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	60,921	$58,\!122$	61,206	$57,\!837$	60,985	$58,\!058$

Table 5.1: Testing Mechanisms

Note:

This table presents β from equation (3) across different subsamples. Columns (1) and (2) split the sample into below- and above-median HTF serial correlation. Columns (3)–(6) use two alternative proxies to separate areas by below- and above-median expectations of future adaptation. Measures of local climate beliefs are drawn from the Yale Climate Opinion Survey. Standard errors are clustered at the county level. *p < 0.1; **p < 0.05; ***p < 0.01.

adaptation efforts (Butler 2011). Table 5.1 columns (3) and (4) show that, indeed, the impact of recent HTF exposure has much larger impact on the price-rent ratio in places with higher expectation for government intervention.¹⁶

In columns (5) and (6), we test the future adaptation channel using an alternative proxy: beliefs about climate change impact that are not associated with emotional concern, which likely reflect individuals' anticipation of effective adaptation measures. For this, we leverage two questions from the Yale Climate Opinion Survey: the share of respondents who believe that global warming will start to harm people in the US within the next 10 years (the "Timing" variable) and the share who report being worried about climate change (the "Worried" variable). We regress the Timing variable on the Worried variable and use the residual from this regression as a proxy for confidence in future adaptation.¹⁷ Importantly, because the Timing variable specifically captures beliefs about climate change affecting lives within the next 10 years, we can rule out the possibility that individuals who believe in climate change but are not worried because they perceive it as a too distant threat. This allows us to more confidently interpret a lack of concern—despite expectations of near-term harm—

¹⁶The Yale survey asks similar questions about other levels of government, including state, local, and Congress. We find that the results are highly consistent regardless of which level-specific variable is used.

 $^{^{17}}$ To run this regression, we first aggregate the county-year-level data to the county level by averaging values across years.

as indicative of belief in effective adaptation. Similar to columns (3) and (4), we find that a group with stronger opinions on adaptation proxies exhibit higher price-rent ratio increase due to the recent HTF exposure.

5.2 Chronic vs. Permanent Inudation

Our central findings indicate that the risk of HTF has larger impacts on rents than housing prices. This contrasts with earlier studies that have documented substantial price discounts (but typically no effects on rents) for properties exposed to the risk of permanent inundation by the end of the century (Bernstein et al. 2019, Baldauf et al. 2020, Giglio et al. 2021). Such a disconnect implies that the market treats HTF and permanent inundation as unrelated phenomena. This is particularly surprising given that HTF—essentially chronic inundation—and permanent inundation are driven by fundamentally similar physical processes. As detailed in Section 3.1, the two distinct inundation mapping products are developed using identical modeling approaches (NOAA 2017, n.d.).¹⁸

Such a disconnect may stem from at least two different sources. First, individuals tend to overlook gradual environmental changes—a phenomenon often referred to as the "boiling frog" effect—and instead focus on abrupt, binary status shifts (Liu et al. 2025). Sea level rise is inherently a gradual process, often manifesting first as an increasing number of intermittent flooding events before culminating in permanent inundation. However, as people become acclimated to these changing conditions, they may normalize the risk and consequently underreact, discounting the significance of what is, in effect, a clear early warning signal. In contrast, the risk of permanent inundation may still provoke behavioral responses due to its greater perceived salience.

Another possibility is that communication around sea level rise has failed to convey the underlying physical connectivity. For instance, NOAA's inundation maps for HTF and permanent inundation are presented as distinct products, and unless one closely reviews the technical documentation, it is difficult to recognize their methodological overlap. Similarly, IPCC reports, particularly earlier assessments, have emphasized long-term projections with a particular attention to permanent inundation (IPCC 2007, IPCC 2014), which may have inadvertently downplayed the immediacy and progressive nature of sea level-related impacts.

 $^{^{18}\}mathrm{See}$ Section 3.1 for more details.

6 Conclusion

Driven by climate change, sea levels are rising rapidly, and many coastal communities are already experiencing serious disruptions to daily life and economic activity due to HTF. Alarmingly, HTF exposure is projected to increase exponentially over the next two decades, posing significant threats to the livability of coastal areas. Yet despite its potentially severe consequences, little is known about how HTF affects coastal housing markets.

Leveraging plausibly exogenous variations in HTF occurrences as an information shock, we find that one additional day of HTF in the past 12 months reduces housing prices and rental rates by 0.09% and 0.23%, respectively. A simple asset pricing framework suggests that the smaller decline in housing prices—relative to rents—reflects market expectations of a future rebound in rental income. We further show that this pattern is particularly pronounced in areas with stronger expectations of government-led adaptation. These findings underscore the potential risk of policy-induced moral hazard.

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A Additional Tables and Figures



HTF Inundation Map (Atlantic)

Figure A.1: Inundation Map (Atlantic Region)

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Figure A.2: HTF Serial Correlation. These figures show the correlation between HTF frequency in year t and year t-1 using (a) binned scatterplot and (b) residualized binned scatter plot where year and gauge dummies are used for residualization. Panel (c) shows the distribution of gauge-specific serial correlation.

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Figure A.3: Location of NOAA Gauge Stations. This figure depicts 84 NOAA gauge stations within the contiguous US that has flood thresholds from Sweet et al. (2018).

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Figure A.4: Impulse Response Function Estimates. These figures plot β_k estimates from equation (2) a month-specific HTF days and (a) log of housing prices and (b) rents.

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