Annoyed, but Not Alarmed: Intermittent Inundation Risks and the Coastal Housing Market

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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 year-to-year variation in HTF, we find that HTF exposure reduces both rents and housing prices, but the effect on rents is three times larger—suggesting that homebuyers anticipate a future recovery in rental values. We show that this optimism likely stems from expectations of government-led adaptation investments. These findings underscore the risk of policy-induced moral hazard.

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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 road networks and thus 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. We leverage year-to-year variation in HTF frequency as a source of information shocks that affect individuals' beliefs about future HTF exposure. 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 exercise, we first introduce a simple Gordon growth model, where housing prices are determined by the present value of current and future rental income (Campbell and Shiller 1988, Campbell et al. 2009). The model illustrates how new information about HTF frequency can shift individuals' beliefs about future risk, thereby affecting expected rental income and current housing prices. Crucially, the relative impact on rents and prices depends on how the information is interpreted. For instance, when individuals interpret information such as a spike in HTF days as an early indicator of worsening or permanent inundation, the impact will be more pronounced on housing prices than on current rents. In contrast, if the shock is perceived as temporary, or even if seen as persistent but expected to be mitigated through future adaptation, the effect may fall more heavily on rents than on prices.

To take these insights to data, we compile daily water level data from 84 NOAA gauge stations 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

dataset is linked with monthly zip code level data on housing prices, rents, and housing inventory. To shed light on mechanisms, we use survey data on local climate change opinions. For identification, we exploit plausibly exogenous year-to-year variations in the number of days with HTF.

We start our empirical exercise by estimating the impact of 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 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 increase, suggesting that the limited price adjustment is unlikely to be driven by reduced transaction activity. We also show that our 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 HTF days in the past 48 months or scientific forecasts of future HTF frequency.

Finally, we explore the source of market optimism about future rents. Specifically, we test whether the impact of HTF exposure on price-rent ratio varies systematically with local climate change opinions, including beliefs, policy expectations, and emotional responses. We find that the increase in the price–rent ratio—namely, HTF's impact is larger (in magnitude) for rents—following recent HTF exposure is not driven by disbelief in climate change; in fact, areas with greater skepticism tend to exhibit *smaller* increases in the price-rent ratio. Instead, the effect is more pronounced in areas where individuals express stronger expectations for future government actions, suggesting that optimism about mitigation efforts, rather than denial of risk, is the primary driver. This highlights the importance of designing policies that do not encourage individuals to take on greater risks.

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. As a result, these papers implicitly assume no housing market response between initial capitalization and eventual inundation, even though such intermediate risks are likely to influence coastal markets much earlier. 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 the intermediate stages. Juxtaposing our findings with previous studies suggests that markets may treat intermittent 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 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), and emphasizes the importance of designing a policy that aligns social and private incentives.

This paper proceeds as follows. Section 5 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 5.1 explores the mechanism. Section 6 concludes.

2 Conceptual Framework

To understand how an information shock influences subjective beliefs about HTF risk—and thereby affects housing prices and rents—we consider a Gordon growth model in equation (1) (Campbell and Shiller 1988, Campbell et al. 2009). In this framework, housing price P in time $t = 1$ is determined by the concurrent and future rental income, where future reward is discounted by δ, which reflects the required return (i.e., risk free interest rate and housing premia).[1]

$$P_1 = \sum_{t=1}^{\infty} \delta^t R_t \tag{1}$$

Rent at time t is $R_t = r(z_t, E_t[F_t])$. That is, rent is a function of z_t, housing characteristics and amenities at time t, and subjective HTF risk $E_t[F_t]$, namely an *expected* number of days with HTF over the rental period t, where the expectation is formed at the beginning of t. Housing units with higher amenity values will have higher rental rates ($\frac{\partial r}{\partial z} > 0$) and higher expectation on the HTF days will lower rental rates ($\frac{\partial r}{\partial E[F]} < 0$). Note, r does not have a time subscript, which implies that the relationships between R and its determinants (z and $E[F]$) are assumed to be stable over time. $E_t[F_t]$ is formed by ξ_t, a set of available information on HTF risk at time t.

Suppose that new information arrives at $t = 1$, which increases $E_1[F_1]$. Then, rent income in $t = 1$ will decline by $\frac{\partial r}{\partial E[F]} \frac{dE_1[F_1]}{d\xi_1}$. This information shock will also affect future rent flows as equation (2). Moreover, it will also affect housing price as equation (3), reflecting present value of the reduction in expected future rental income.

$$\frac{\partial R_t}{\partial \xi_1} = \frac{\partial r}{\partial E[F]} \frac{dE_1[F_t]}{d\xi_1} \tag{2}$$

[1] For simplicity, we ignore other dimensions of a standard Gordon model such as outside investment opportunities and tax implications.

$$\frac{\partial P_1}{\partial \xi_1} = \sum_{t=1}^{\infty} \delta^t \frac{\partial R_t}{\partial \xi_1} = \sum_{t=1}^{\infty} \delta^t \frac{\partial r}{\partial E[F]} \frac{dE_1[F_t]}{d\xi_1} \tag{3}$$

To highlight the relationship between new information and housing market dynamics, we impose a structure and assume that the impact of information shock on expected HTF days propagates proportionally over time.[2] Specifically, we posit: $\frac{dE_1[F_t]}{d\xi_1} = \frac{dE_1[F_1]}{d\xi_1}\lambda^t$. Then, we can simplify equations (2) and (3) to $\frac{\partial R_t}{\partial \xi_1} = \frac{\partial r}{\partial E[F]} \frac{dE_1[F_1]}{d\xi_1}\lambda^t$ and $\frac{dP_1}{d\xi_1} = \frac{dr}{dE} \frac{dE_1[F_1]}{d\xi_1} \sum_{t=1}^{\infty} \delta^t \lambda^t = \frac{dR_1}{d\xi_1} \frac{1}{1-\delta\lambda}$. To connect with our empirical analysis, it is convenient to convert these changes in prices and rents in percentage terms. For that, suppose R is the baseline rental rate and $P = \frac{R}{1-\delta}$, is the baseline price. Then, the percent change in price $\frac{1}{P}\frac{dP_1}{d\xi_1} = \frac{1}{\frac{R}{1-\delta}} \frac{dR_1}{d\xi_1} \frac{1}{1-\delta\lambda} = \frac{1}{R} \frac{dR_1}{d\xi_1} \frac{1-\delta}{1-\delta\lambda}$. Note, because the percent change in rent is $\frac{1}{R}\frac{dR_1}{d\xi_1}$, $\frac{1-\delta}{1-\delta\lambda}$ is the ratio of percent change in prices and rents.

Importantly, the value of λ governs the relative size of HTF risk impacts on rents and housing prices. Specifically, when $\lambda = 1$, $\frac{1-\delta}{1-\delta\lambda} = 1$, which indicates that the HTF risk should have the same impact (i.e., magnitude) on rental rates and housing prices (full capitalization). $\lambda = 1$ implies that individuals view the expectation of the current state as the best predictor of the future state under current information set (i.e., $E_1[F_1] = E_1[F_t]$). That is, individuals perceive recent experiences as a persistent shift in underlying distribution.

When $\lambda > 1$, the impact of information shock on the housing price is larger than the impact on current rents (i.e., $\frac{1-\delta}{1-\delta\lambda} > 1$). Such an overcapitalization implies that individuals view information shock at $t = 1$ as a signal of aggravating sea level rise, which may culminate as a permanent inundation. Specifically, for large T, $\frac{dE_1[F_T]}{d\xi_1} = \frac{dE_1[F_1]}{d\xi_1}\lambda^T$ will reach 1, which implies that rental income beyond T will be completely wiped out due to the uninhabitable condition.

Finally, when $\lambda < 1$, the impact of new information on the housing price is smaller than the impact on current rents (i.e., $\frac{1-\delta}{1-\delta\lambda} < 1$). Undercapitalization implies that individuals anticipate a future rebound in rental rates. Such an optimism can arise when (1) market participants may expect that future HTF frequency will not remain elevated, reflecting, for example, mean-reverting beliefs or (2) buyers engage in moral hazard, anticipating future public flood mitigation efforts such as seawalls or

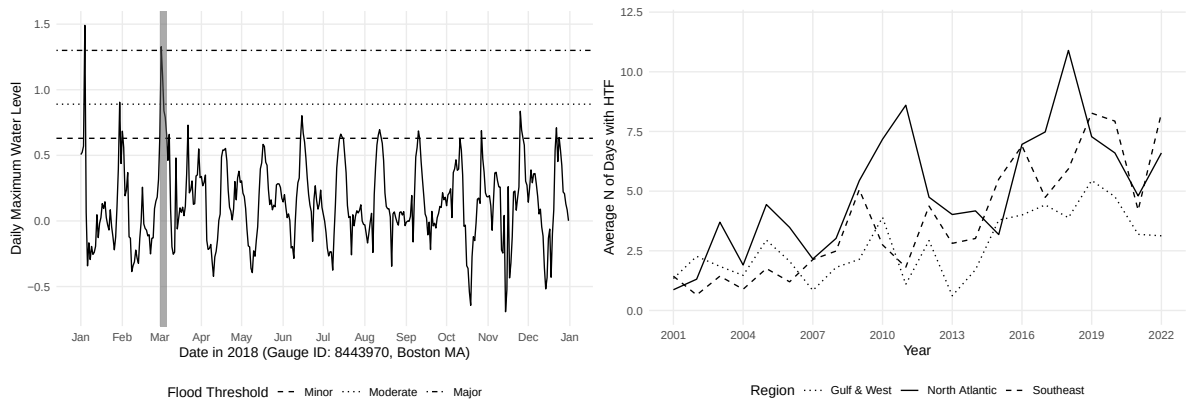
[2] We assume proportional propagation of the information shock through a single parameter λ for tractability. However, the qualitative conclusions—whether the information shock leads to full, over-, or under-capitalization—do not depend on this specific functional form. More generally, our results hold as long as the impact of new information on expected future HTF frequency monotonically amplifies, persists, or decays over time: that is, the key determinant is the pattern of the sequence $\{\frac{dE_1[F_t]}{d\xi_1}\}_{t\geq 1}$: increasing for over-capitalization, constant for full capitalization, and decreasing for under-capitalization.

other large-scale investments.

This dynamic is consistent with the effects of belief models such as adaptive learning or Bayesian learning with strong mean-reverting priors, although our reduced-form λ-propagation framework abstracts from the full structure of these updating processes. Another possibility is that buyers engage in moral hazard by anticipating future flood mitigation efforts, such as seawalls or other public investments (Baylis and Boomhower 2023).[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 information set (ξ) is past HTF exposure. This approach follows a volumenous 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 for ξ, we demonstrate that our results are robust to alternative choices, including a 48-month exposure window or scientific forecasts of HTF frequency.

One potential concern with using recent HTF exposure as a proxy for ξ 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 shifting expectations about future HTF risk.



(a) HTF Measurement (b) HTF Days by Region

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 2001–22 by region.

3 Background and Data

3.1 High Tide Flooding

HTF: measurements, trends, and impacts.[4] High-tide flooding (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 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 ± 3-day window of a moderate or major flood event as non-HTF, even if water

[3]While climate adaptation can, in principle, occur at both the private and public levels, the nature of strategies specific to sea-level rise—protection, accommodation, ecosystem-based adaptation, coastal advance, and retreat—means that expectations about adaptation are often closely tied to expectations of public investment (IPCC 2022). For a detailed discussion of these strategies, see IPCC (2022).

[4]Much 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.

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—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 = (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 structural similarity in map generation highlights the common underlying physical process of HTF and SLR: the key distinction is that HTF results in intermittent inundation, whereas SLR leads to 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). For example, as illustrated in Figure 3.1 (b), the average number of HTF days per year was around 2–3 during the 2001–03 period, but this has increased to 3–8 days in the 2020—22 period. Further, this trend is expected to accelerate—by mid-2040, many cities along the Atlantic Coast are projected to

[5]Accessed 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.

[6]Consistent 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).

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

experience 50–100 of HTF annually (Thompson et al. 2021).

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).

HTF as a research design. Interpreting Figure 3.1 (b) solely in terms of overall trends obscures substantial temporal and geographic variation in HTF occurrences. The Atlantic Coast, for instance, has experienced a much steeper increase compared to the Gulf or Pacific regions, and significant year-to-year fluctuations persist within each region. Appendix Figure A.2 further shows that, after controlling for year and gauge fixed effects, HTF exhibits only weak serial correlation, resembling a plausibly 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 (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

[8] Ad 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.

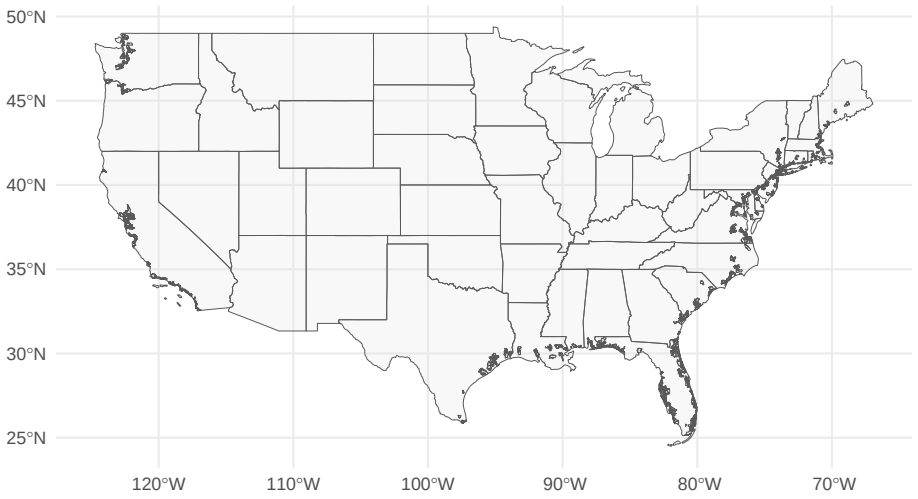


Figure 3.2: Map of the Study Area. This figure shows our main sample, which consists of 1,469 zip codes that have non-missing ZHVI and ZORI data over 2015–21 and have an overlap with the NOAA inundation map.

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 et al. (2022). Our primary sample 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).[10]

[9]For 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).

[10]These 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.

Climate opinion. To explore mechanism, we collect county-level climate opinion data from the Yale Climate opinion survey. The data documents public 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).[11] 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.[12] These variables are (1) the share of respondents who believe that climate change will start to harm people in the US within the next 10 years; (2) the share who report being worried about climate change; and (3) the share of people who believe that the President should do more to address climate change.

3.3 Summary Statistics

Table 3.1 shows summary statistics for key variables used in our empirical exercises from our main sample. 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 0 miles, indicating that HTF exposure is well-measured for most zip codes. For some zip codes that are affected 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

[11] More details can be found at https://climatecommunication.yale.edu/visualizations-data/ycom-us/ (accessed on May 7, 2023).

[12] Because 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.

Table 3.1: Summary Statistics for Key Variables

Variables	Min.	Max.	Median	Mean	Std.Dev.	N
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 to the Coast (Miles)	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

larger than that of moderate or major floods. Also, the difference between the mean (20.9) 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 subjective HTF risk on housing market outcomes, we estimate the regression model in equation (4).

$$log(Y_{czmt}) = \beta F_{zmt} + \alpha_z + \theta_{ct} + \theta_m + \epsilon_{czmt} \tag{4}$$

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 shocks to ξ in equation (3), 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 is an empirical

analogue of equation (3). Notably, this 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, equation (3) indicates 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 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 substantially undercapitalized into 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 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

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

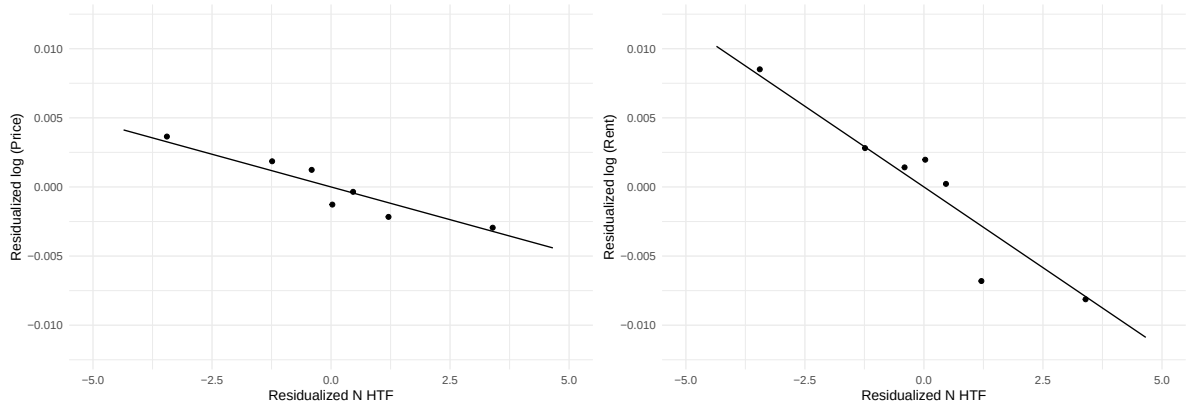
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var.:	log(Price)	log(Rent)	log (P/R)	log (Active Listings)	log (New Listings)	log (DOM)
HTF Days (Past 12 Months)	-0.0009***	-0.0023***	0.0014***	-0.0024	-0.0004	0.0003
	(0.0002)	(0.0004)	(0.0003)	(0.0015)	(0.0013)	(0.0008)
Zip Code	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes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

Note:
This table presents the effect of HTF on the housing market using equation (4) 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. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

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.

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 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 (4).

In Table 4.2, we conduct a series of robustness checks. 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



(a) Housing Prices (b) Rental Rates

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 year 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.

price-rent ratio from our preferred specification. This is plausible given that year-to-year variations in HTF occurrences are plausibly random. In column (2), we control for more granular seasonality. Specifically, we include zip code by month fixed effects, which can account for local housing market or HTF seasonality, 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 (4) 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, 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.[13] 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.

[13]Because ZORI data starts in 2015, we cannot use price-rent ratio as an outcome variable for this exercise.
[14]These 11 states are CT, DC, DE, MA, MD, ME, NH, NJ, NY, RI, and VA.

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

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var.:	log (P/R)	log (P/R)	log(Price)	log (P/R)	log(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)		
HTF Days (Past 48 Months)					-0.0012**	
					(0.0004)	
HTF Days (Forecast)						0.0020
						(0.0023)
Sample	Main	Main	2000-14	Northeast	Main	2018–21
Controls	Yes	No	No	No	No	No
Zip Code	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	No	Yes	Yes	Yes	No
Year-County	Yes	Yes	Yes	Yes	Yes	Yes
Month-County	No	Yes	No	No	No	No
Observations	119,043	119,043	246,777	75,255	119,043	5,799

Note:
This table presents the effect of HTF on the housing market using alternative specifications. Column (1) includes 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. Column (2) includes more granular County by Month fixed effects. Column (3) reports the impact of HTF on housing prices over 2000–14. Column (4) repeat Table 4.1 column (1) using zip codes that are in the 11 Northeast states. Columns (5)-(6) show results from alternative information sources. Standard errors are clustered at the county level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Columns (5) and (6) examine the robustness of our results to alternative measures of information set ξ. In column (5), we extend the belief formation window by using HTF exposure over the past 48 months instead of 12, and find the impact of HTF on housing prices nearly identical to the main specification. This suggests that even if homebuyers form beliefs based on a longer history (e.g., 48 months) than renters (e.g., 12 months), the undercapitalization result persists, which indicates that undercapitalization is unlikely to be driven by systematic differences between homebuyers and renters in how they form expectations about future HTF risk.[15]

Finally, in column (6), 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

[15]In column (5), we use log (housing price) as an outcome variable to allow different information sources for homebuyers and renters (i.e., homebuyers update beliefs based on longer history than renters). When we replace an outcome variable to log (price-rent), we find a very close coefficient at 0.0015 (s.e. = 0.0008) to results from our main specification.

use NOAA's HTF annual outlook data, available for the years 2018–21.[16] To match this data's annual frequency, we aggregate housing prices accordingly and regress them on the forecasted number of HTF days. While the coefficient estimate is imprecise due to limited sample size, the impact of expected HTF days on price-rent ratio is slightly larger at 0.002.

5 Discussion

5.1 Mechanism

Section 2 highlights that (1) undercapitalization arises when the market holds optimistic beliefs about future HTF exposure, and (2) such optimism may arise due to optimism about future HTF frequency or future adaptation actions. In Table 5.1, we empirically test which of these mechanisms best explains the observed pattern. To focus on the extent of capitalization, we use log of price-rent ratio as outcome variables.

We first test whether optimism about future HTF frequency (e.g., mean-reverting expectation) is the main driver. For this analysis, we use county-level data from the Yale Climate Opinion Survey on 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).[17] Specifically, we take the average of this variable across all available years for each county and divide the sample into above- and below-median belief groups and re-estimate equation (4) separately for each. If this is the main driver, we expect to find a smaller coefficient (i.e., higher capitalization) for the high denial (i.e., below-median belief) group. However, columns (1) and (2) report the opposite: the magnitude of undercapitalization is twice as large for low denial group.

Next, we examine whether expectations on future adaptation is the main driver. To proxy for adaptation expectations, we use beliefs about climate change that are not associated with emotional concern. Specifically, we leverage data from the Yale Climate Opinion Survey and regress the Timing

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

[17] Previous studies have used the share of respondents who believe that global warming is happening as a measure of climate change belief (Baldauf et al. 2020, Murfin and Spiegel 2020). These studies typically focus on sea level rise risk projected for the end of the century. In contrast, our paper examines high-tide flooding, which represents a much more immediate threat. Thus, our chosen variable—perceptions of near-term harm—seems more relevant in our empirical setting. That said, our results remain robust: we find very similar patterns even when substituting the belief-in-happening variable into our analysis.

Table 5.1: Testing Mechanisms

	(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)	0.0020***	0.0010***	0.0012***	0.0017***	0.0011***	0.0019***
	(0.0005)	(0.0002)	(0.0004)	(0.0004)	(0.0002)	(0.0006)
Sample	Low Denial	High Denial	Low Adapt	High Adapt	Low Policy	High Policy
Zip Code	Yes	Yes	Yes	Yes	Yes	Yes
Year-County	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes
Observations	59,689	59,354	60,985	58,058	61,206	57,837

variable on the share who report being worried about climate change.[18] We then use the residual from this regression as a proxy for confidence in future adaptation with the idea that some individuals may recognize that climate change will cause harm in the near future but remain relatively unconcerned, possibly because they anticipate effective adaptation measures. Importantly, because the Timing variable specifically captures beliefs about climate change causing harm 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—as indicative of belief in effective adaptation. Table 5.1 columns (3) and (4) show that, indeed, undercapitalization is substantially more prevalent in a group with high expectation for adaptation.

In columns (5) and (6), we test the future adaptation channel using an alternative proxy: 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 adaptation efforts (Butler 2011). Similar to columns (3) and (4), we find that a group with stronger opinions on government intervention

[18]To run this regression, we first aggregate the county-year-level data to the county level by averaging values across years.

exhibit higher magnitude of undercapitalization.[19]

5.2 Intermittent vs. Permanent Inudation

Findings from our paper suggests that the risk of HTF is undercapitalized into the housing market. This contrasts with earlier studies that have documented substantial price discounts (but typically no comparable 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 intermittent inundation—and permanent inundation are driven by fundamentally similar physical processes. In fact, the two distinct inundation mapping products are developed using identical modeling approaches (NOAA 2017, n.d.).[20]

Earlier studies suggest that this disconnect may stem from several 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 between HTF and permanent inundation. For instance, NOAA's inundation maps 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.

[19]The 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.

[20]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 gauge-based data on HTF occurrences, 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 model suggests that this undercapitalization reflects market expectations of a future rebound in rental income. We further show that undercapitalization is particularly pronounced in areas with stronger expectations of government-led adaptation. These findings underscore the risk of policy-induced moral hazard.

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A Additional Tables and Figures

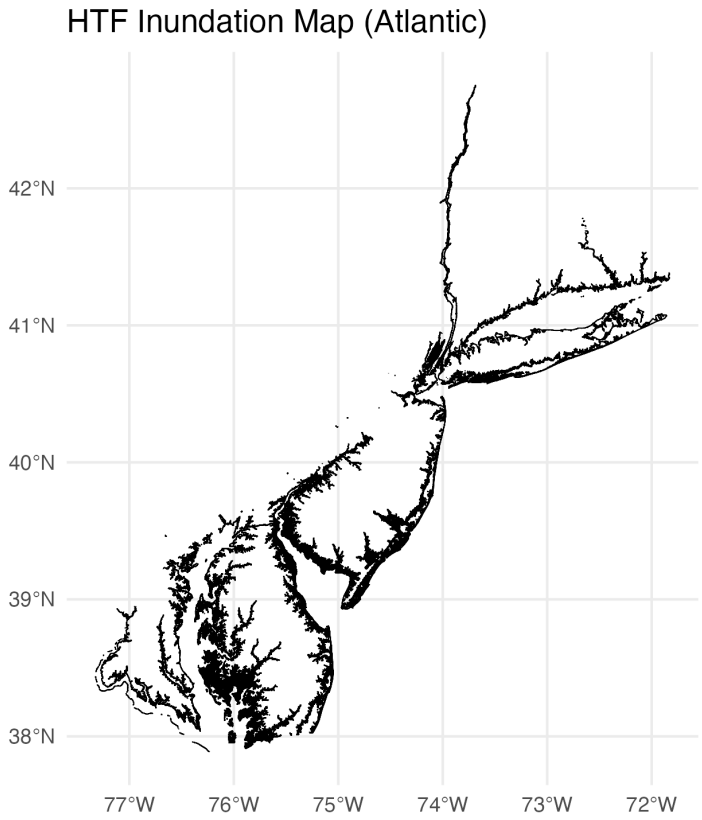
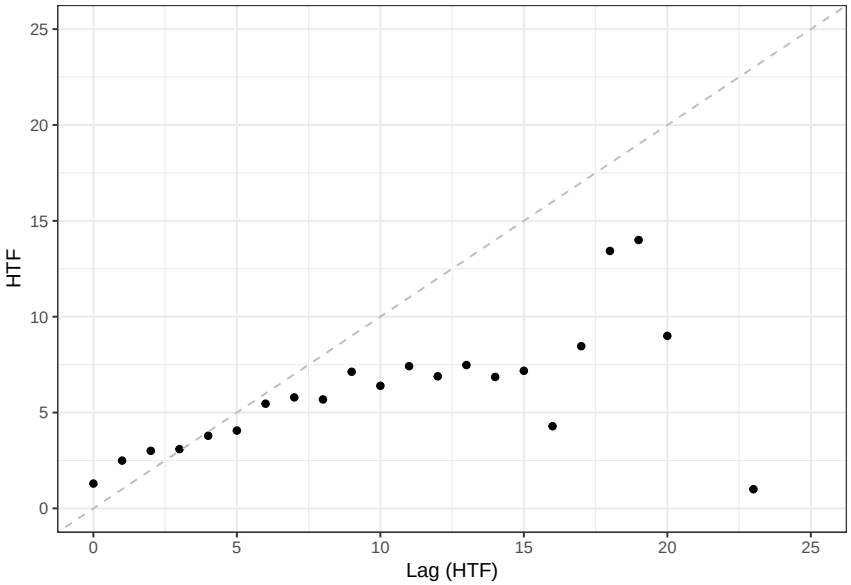
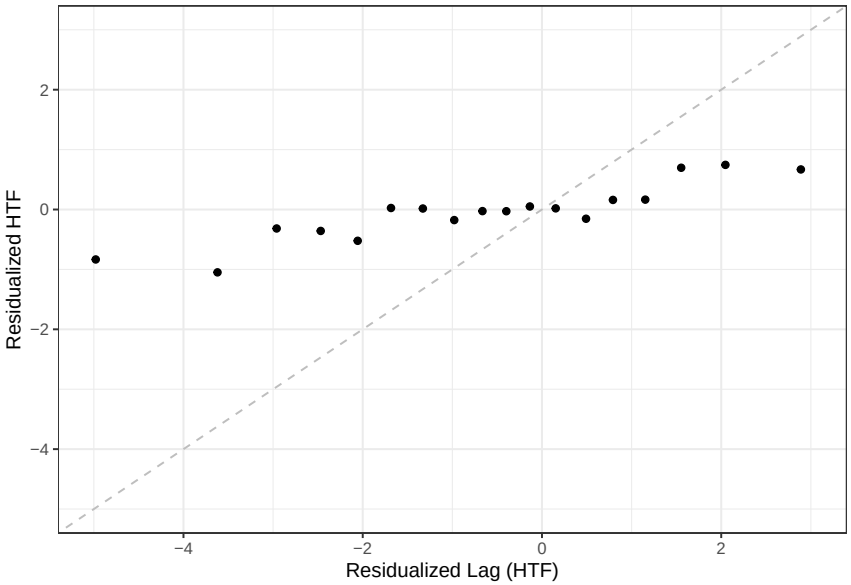


Figure A.1: Inundation Map (Atlantic Region)

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(a) Without FE



(b) With Year and Gauge FEs

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.

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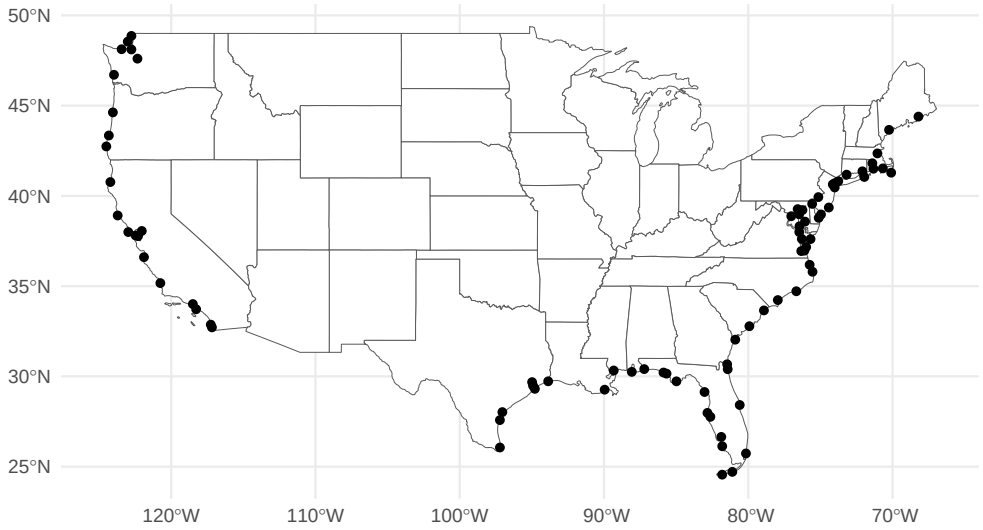


Figure A.3: Location of NOAA Gauge Stations. This figure depicts 84 NOAA gauge stations within the contiguous US that has flood thresholds from Sweet et al. (2018).

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