Does Market Price Sea Level Rise Risk? Evidence from High-Tide Flooding

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Abstract

Scientific findings suggest that sea level rise (SLR) is imposing a serious threat to the sustainability of coastal communities, but the evidence is mixed as to whether the market adequately prices the risk. In this paper, we leverage a novel source of identification—plausibly random variations in high tide flooding, a direct consequence of SLR—to credibly estimate the impact of SLR. We find that exposure to one additional day of HTF in the past 12 months reduces average housing price in the affected zip codes by a mere 0.08% (or 0.43% at the mean number of days with HTF). We then estimate the impact of HTF on climate beliefs to find that the strength of support for government mitigation policies explains such a small capitalization effect. These findings underscore the risk of policy-induced moral hazard.

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1 Introduction

Numerous scientific studies find that sea level rise (SLR) is imposing an existential threat to the coastal communities (Witze 2018, Taherkhani et al. 2020, Sweet et al. 2022). While economic theory suggests that an efficient market factors in such a risk into the housing prices, existing works produce mixed results on price capitalization (Bernstein et al. 2019, Baldauf et al. 2020, Murfin and Spiegel 2020, Keys and Mulder 2020). The lack of consensus might (at least partly) reflect, as the literature has aptly pointed out, an identification challenge: while there are substantial cross-sectional variations in SLR exposure within the US, defining temporal variation is difficult because SLR is a long-term and continuous process without clear "treatment timing". Further, the lack of consensus on the housing price adjustment might not be surprising given existing evidence on behavioral biases or information frictions in the housing market, which will limit the extent of market participants' ability to take the SLR risk into account (Bin and Landry 2013, Lee 2021). This is unfortunate given that price signal can be a powerful climate change adaptation tool (Anderson et al. 2019).

In this paper, we leverage a novel variation in SLR exposure to (1) test whether and to what extent market prices the risk and (2) investigate mechanisms that hinders price adjustments with an emphasis on people's belief about future climate policies. Our empirical exercise leverages high-tide flooding (HTF), a temporary inundation of low-lying areas in coastal communities during a full moon period, which has become more prevalent in recent years due to SLR (Sweet 2018).[1] We argue that HTF provides a unique opportunity to credibly identify the impact of SLR for two reasons. First, HTF is a direct consequence or a symptom of SLR that translates a rather abstract SLR into a hands-on and highly salient experience. For instance, evidence shows that HTF seriously disrupts mobility and business operations by making roads impassible even during sunny days (Hino et al. 2019, Hauer et al. 2021, Lee et al. 2023). Thus, an effect of HTF on the housing prices can be interpreted as an impact of SLR when market participants are well aware of the SLR risk. Second, it has rich temporal and spatial variations, which allows us to exploit year-to-year deviations in location specific HTF exposure to study the impact of SLR. This mirrors an approach pioneered by Deschênes and Greenstone (2007) that leverages year-to-year variation in location-specific temperature to study the impact of climate change.

[1]For instance, NYC had 17 days of HTF in 2017 alone, and many cities along the east coast are projected to experience 50+ days of HTF in the next 10–15 years (Thompson et al. 2021).

For the empirical analysis, we compile daily water level data from 84 NOAA gauge stations in the contiguous US and compare them with the site-specific flood thresholds to construct historical HTF events data. We link this with zip code level monthly housing price data from Zillow (2015-2021), and county level climate beliefs and opinions from Yale Climate Opinion Maps (2018-2021) (Howe et al. 2015). For estimation, we leverage plausibly exogenous location-specific year-to-year deviations in the number of days with HTF.

We start our empirical exercise by estimating the impact of the HTFs on the housing prices. We find that exposure to one additional day of HTF in the past 12 months reduces average housing price in the affected zip codes by 0.08%. At the mean annual number of HTFs for the zip codes in our sample over 2015–2021 (5.5), 0.08% translates into a 0.43% (or $1,958) lower housing price. We then compare the estimate with the impact of HTF on the rental rates from a companion paper (Lee et al. 2023), and find that only 1/3 of the rental rates adjustment capitalizes into the housing price.

We then introduce a state-dependent (i.e., disaster versus no-disaster states where disaster represents large events such as hurricane) housing price model, which builds on Gordon growth model, to investigate the mechanism behind the puzzle—namely, why only 1/3 of rental rate change is reflected into the housing price (Campbell and Shiller 1988, Campbell et al. 2009). The model first shows that HTF can reduce housing prices through two different channels. First, by increasing the subjective probability of the disaster state, which produces lower rental income (i.e., pricing of future climate change risk). Second, by reducing rental rates in no-disaster state by incurring disruptions in daily lives (i.e., lower flow-utility in the no-disaster state due to the HTF). The model predicts that the price capitalization is likely to be small when (1) HTF fails to increase the subjective probability of the disaster state and (2) when people are optimistic about future rental rates in the no-disaster state.

To empirically test these predictions, we estimate the impact of HTF on three different types of climate opinions from the annual Yale Climate opinion survey data (Howe et al. 2015). We find that at the mean annual number of HTF for the counties in our sample over 2018–2021 (6.8), the fraction of population discussing climate change related issues goes up by 1%. Further, the fraction of population concerned about climate change slightly increases (0.13%) although the magnitude is a fraction of the increase in the fraction of population discussing it. We argue that this (at least partly) reflects people's expectation about mitigation measures provided by governments. Namely, we find that at the mean annual number of HTF, the fraction of population who think the president (or local government) should “do more to address global warming” increases by 1.3% (0.4%). Consistent with this, we find that the housing price adjustment is null from states that have stronger opinion about the role of government in climate change mitigation. Further, these changes in opinion are in general much stronger in the coastal states rather than their inland counterparts.

This paper contributes to two different strands of literature. First, it is related to earlier works testing whether the market incorporates SLR risk into the housing market. While some find a substantial decline in the price for the SLR exposed properties (Bernstein et al. 2019, Baldauf et al. 2020), others find a null or delayed effect (Murfin and Spiegel 2020, Keys and Mulder 2020). Our paper complements the existing works by leveraging a novel source of variation that could be useful in studying the SLR risk. Further, by linking the housing price impact with the rental impact and climate beliefs, we show two separate channels behind attenuated price capitalization.

Second, this paper extends the existing literature that studies the source of market inefficiency regarding climate risk. While earlier works have emphasized the role of imperfect information (Lee 2021, Hino and Burke 2021, Bakkensen and Barrage 2021) or behavioral biases (Bin and Landry 2013, Gallagher 2014), 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), and emphasizes the importance of designing a policy that aligns social and private incentives.

This paper proceeds as follows. Section 2 discuss research design aspect of HTF, details the data sources and provides summary statistics. Section 3 analyzes the impact of HTF occurrence on housing prices and provide conceptual framework, while Section 4 studies the impact of HTF on climate opinions. Section 5 concludes.

2 Background and Data

2.1 High-Tide Flooding As a Research Design

Previous efforts to identify the SLR effect. To test whether a market is efficiently pricing SLR risk, at least two conditions should be satisfied. First, there should be plausibly random variations in the

SLR exposure. Second, market participants should be aware of the SLR variations. Per the first condition, previous works on the impact of SLR have mostly relied on cross-sectional variations in the SLR (or relative SLR) exposure (Bernstein et al. 2019, Baldauf et al. 2020, Murfin and Spiegel 2020, Keys and Mulder 2020) because of a fundamental research design challenge: SLR is a continuous process, and defining a "treatment date" is difficult.[2] And because the SLR exposure is correlated with various confounding factors such as water front amenity, cross-sectional variation faces identification challenges. To add a temporal variation, some papers have used 2014 as a critical point because IPCC released their 2013 climate assessment report in early 2014. However, pre and post 2014 comparison is at best suggestive given that the continuous nature of information treatment. That is, scientific findings that forms the basis of IPCC report has been continuously released even before 2014, and even after 2014, IPCC has released a few high-profile reports. Another approach to overcome this problem would be using spatial discontinuities of SLR exposure, but it is hard to believe that an average home buyer would recognize and take into account such a "border" even if we are willing to make a rather heroic assumption that physically establishing an exact border is feasible (which is plagued with high uncertainty).

About the second condition, prior works generally considered a property is exposed to the SLR risk if "six feet or less of SLR would put the property underwater" (Bernstein et al. 2019, Baldauf et al. 2020), but the effectiveness of simple flood risk disclosure policy suggests that a typical home buyer is not likely to acquire, process, and internalize such information on their own (Lee 2021). In addition to the information friction, home buyers or owners also have behavioral biases that can further impede internalizing such risk (Bin and Landry 2013, Gallagher 2014). These information friction and behavioral biases suggest that even though SLR and climate change have been widely covered in the news media and relevant information has been publicly available, figuring out an implication of such a risk for a specific property is far from immediate for a typical home buyer.

HTF as a manifestation of the SLR. High-tide flooding (HTF), also referred to as recurrent tidal flooding, sunny day flooding, or nuisance flooding, is a type of flooding that happens temporarily in low-lying regions in the coastal communities during full moon periods.[3] Although tidal move-

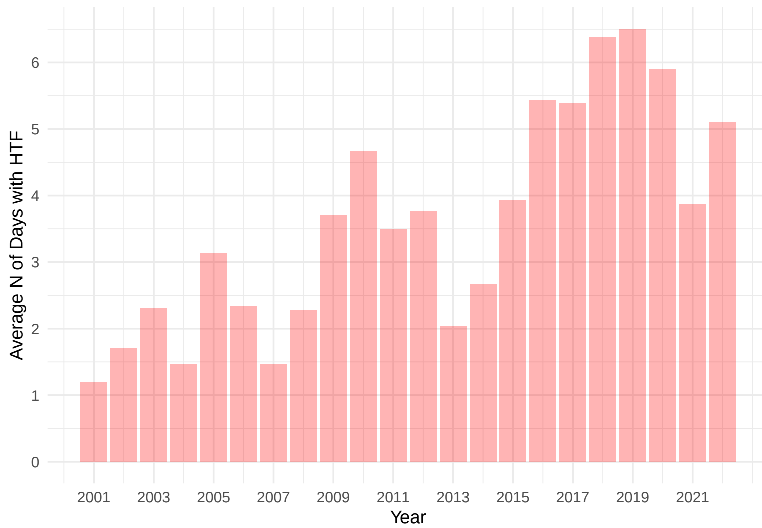
[2] Previous works have also acknowledged these points. For instance, Keys and Mulder (2020) reads "A challenge of studying the effects of climate risk on housing markets is the lack of exogenous variation in exposure. In particular, SLR exposure is correlated with current flood risk, coastal amenities, income, and demographics."

[3] A more detailed description of the HTF can be found in Lee et al. (2023).

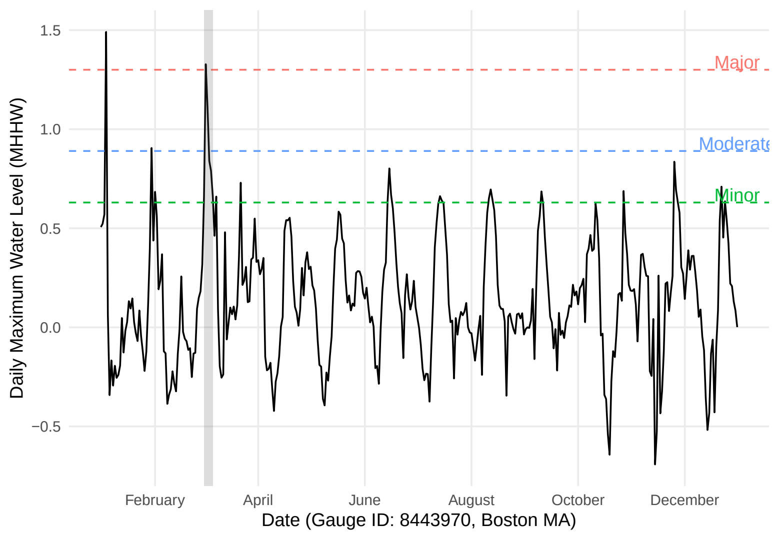
ments are not a recent phenomenon, SLR causes sea waters to gradually over top barriers—both natural and man made—that typically protect coastal areas from flooding. As a result, the average number of days with HTF in the contiguous US has increased over three times in the past two decades (again due to the SLR), as illustrated in Figure 2.1 (a). In addition to this overall trend, the frequency of HTF has been increasing disproportionately along the east coast of the United States compared to the west coast. Consequently, the number of days with HTF is notably higher in cities such as Boston or NYC, with as many as 20 days per year, than in San Francisco, which has a maximum of five days per year. Further, the prevalence of HTF is highest during fall to winter because of the earth and moon alignment (Sweet 2018). These rich physical variations, which are both cross-sectional and temporal, form the foundation of our empirical analysis. That is, by comparing places that have experienced relatively faster vs. slower increase in HTF occurrences, we can more credibly estimate the impact of SLR. Note, this mirrors an approach pioneered by Deschênes and Greenstone (2007) that leverages year-to-year variation in location-specific temperature to study the impact of climate change.

In addition to providing plausibly random realizations of SLR, HTF translates SLR into what a layperson can understand and thus overcomes information friction in flood risk awareness. Further, given its impact on daily lives and its frequency, it is highly salient event that can overcome potential behavioral biases. This feature is useful because it allows us to explore the mechanism behind capitalization effect (or lack of it). Taken together, HTF provides a unique opportunity to empirically test the market efficiency not only because of plausibly random realizations of SLR it provides but also because it is highly salient and frequent phenomenon.

HTF Measurement. The National Oceanic and Atmospheric Administration (NOAA) defines high-tide flooding (HTF) as an event where water levels exceed the minor but remain below the moderate flood threshold (Sweet 2018). To illustrate this definition, Figure 2.1 (b) overlays the daily maximum water height for 2018 from a gauge station in Boston with site-specific flood thresholds. A few things are worth noting. First, the graph shows that the HTF pattern follows the moon phases as the gravitational force is the main driver behind tidal movement. Second, we distinguish a “true HTF” from a “seemingly HTF” that is a precursor or consequence of a larger flood event. For instance, the water level on March 4 in Figure 2.1 (b) satisfies the definition of HTF, but since it is preceded by a major



(a) Average Number of Days with HTF 2001–2022



(b) Detecting HTF using Water Levels Data

Figure 2.1: High Tide Flooding Change Over Time and its Measurement. Panel (a) illustrates the number of days with HTF between 2001 and 2022 averaged over the 84 NOAA gauge stations in the contiguous US. Panel (b) shows how to detect high tide flooding using NOAA daily water levels data.

flood on March 2, it is not a true HTF because it may cause direct damage. Therefore, we exclude such cases within a $\pm$ 3-day window when defining HTF. Additionally, we record separately the dates with water levels above the "moderate" or "major" thresholds to account for the impact of larger flood events.

2.2 Data Description

To understand the impact of high-tide flooding events on the housing price and climate change opinions, we collect and combine three different sets of data.

Housing prices. We use Zillow Home Value Index (ZHVI), which is a dollar-denominated constant-quality measure of a typical home value averaged over the 35th to 65th percentile range for all homes and apartments in a given region.[4] The index adjusts for the likelihood of units being sold to represent property value of the entire market, not just those homes that are currently listed. We use the zip code-level data from March 2015 to December 2021. To connect zip code with HTF events, we link each zip code to the nearest NOAA gauge station. Importantly, given that HTF is unlikely to have any impact for inland areas, we restrict our sample to the zip codes within the 21 coastal states in the contiguous US.[5]

Climate opinion. 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).[6] The first survey was conducted in 2014, and was surveyed again in 2016, 2018, 2019, 2020, and 2021. We use the data from 2018 to 2021 to minimize the impact of survey method updates over time.[7] While the data asks rich set of questions, we focus on six questions that can be grouped into three categories: (i) exposure to and engaging in climate change related information and discussion; (ii) subjective perception about climate change; and (iii) attitude about climate change policies.

Water levels. We build data on coastal floods using the NOAA water levels data from 84 gauge stations in the contiguous US (See Appendix Figure A.1 for gauge station locations). We retrieve ver-

[4] For more detail, see https://www.zillow.com/research/methodology-neural-zhvi-32128/ (accessed on Mar 7, 2023).

[5] These states are AL, CA, CT, DE, FL, GA, LA, MA, MD, ME, MS, NC, NH, NJ, NY, OR, RI, SC, TX, VA, and WA.

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

[7] Survey estimates has been changed over time by (1) incorporating additional data sets and (2) adding broader population groups into the survey. Specifically, the initial survey was conducted for adults age over 25 but adults aged over 18 were included in the later waves. Through personal communication with the Yale Program on Climate Change Communications, we verified that the survey was stabilized after 2018.

ified daily high water level data from NOAA gauge stations using R package “rnoaa”.[8] The threshold comes from Sweet (2018), which is objective and nationally consistent set of minor, moderate, and major coastal flooding thresholds for each gauge.

2.3 Summary Statistics

Table 2.1 Panel A presents summary statistics for the zip codes overlapping with the NOAA inundation map. A few points are worth noting. First, an average annual housing price for the 2,097 zip codes that has any overlap with the inundation map is $454,346 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 not overlapped with the inundation map ($185,906).[9] The difference in the housing price (at least partly) reflects a premium for higher amenity of being closer to the ocean.

Second, the distance from a zip code centroid to the closest coastal line is on average 12.7 miles while the maximum distance is over 100 miles. While 100 miles seem implausible given that the event is driven by tidal movement, this can happen due to geology. For instance, Florida has a highly permeable limestone bedrock, which means that inland areas can also get inundated during a high-tide period.

In Panel B, we present key variables for the climate change opinion analysis. We first tabulate summary statistics for coastal states for six outcome variables regarding climate change beliefs,[10] which is expressed in terms of the fraction of people who said “Yes” to each question. Interestingly, coastal states do not necessarily seem to have higher exposure to climate change related information, but have higher risk perception and preferences for policy intervention, although the difference is modest. Specifically, while the fraction of population with climate change related media exposure (coastal: 25% vs non-coastal: 27%) or discussion (coastal: 31% vs non-coastal: 31%) show negligible difference, coastal states higher fraction of people think climate change is happening (66% versus 62%) or are worried about climate change (57% versus 54%). Similarly, more people think local officials (54% versus 49%) or the president (54% versus 51%) should do more to address the problem.[11]

[8] For datum, we use mean higher high water (MHHW) because NOAA flood thresholds are constructed in reference to the MHHW datum.

[9] There are 27,016 zip codes in the Zillow dataset where 2,097 of them have positive overlap with the inundation map without missing housing price and HTF information.

[10] We do not include summary statistics from the inland states in Table 2.1 for the interest of space, but average values are discussed below.

[11] The question about president’s role has been added in 2019, so we use 2019–2021 data for the variable.

Table 2.1: Summary Statistics for Key Variables

Variables	Min.	Max.	Mean	Std.Dev.	N
Panel A: Housing Price (2015–2021, Zip code level)					
Housing Price	17,199	4,157,816	454,346	373,814	170,707
% Inundated	0	89.72	3.51	8.25	170,707
Distance to the Coast (Miles)	0.02	113	12.65	14.98	170,707
N High Tide Floods (Past 12 Months)	0	44	5.45	4.76	170,707
N Mod+Large Floods (Past 12 Months)	0	11	0.46	0.98	170,707
Panel B: Climate Opinions (2018–2021, County level)					
% Exposed to Media on Global Warming	10.04	49.23	25.12	6.46	5,072
% Discussed Global Warming	19.41	53.5	31.3	5.29	5,072
% Global Warming is Happening	45.24	86.75	65.54	6.76	5,072
% Worried about Global Warming	39.13	81.99	57.36	7.17	5,072
% Local Officials Should Do More	35.75	72.94	53.73	5.68	5,072
% President Should Do More	32.61	74.32	54.27	6.98	3,804
N High Tide Floods (Past 12 Months)	0	41	6.83	4.92	4,974
N Mod+Large Floods (Past 12 Months)	0	8	0.81	1.55	4,974

Finally, number of floods from each data is presented in both panels. In the housing price dataset, the an average number of HTF in the past 12 months from a given month is 5.5 over 2015–2021 period. Not surprisingly, the frequency of larger flood events are much lower: over the same period, moderate or major flood happened an order of magnitude less frequently. In Panel B, the average number of floods are higher than the corresponding numbers in Panel A because the sample period for the climate opinions dataset excludes years 2015–2018, which, on average, had smaller number of floods.

3 Effect of High Tide Flooding on the Housing Prices

To estimate the impact of HTF on the housing price, we estimate the regression model in equation (1) using zip codes that are overlapping with the inundation map.

$$log(Y_{czmt}) = \beta F_{zmt} + \gamma \mathbf{X}_{zmt} + \alpha_z + \theta_{ct} + \theta_m + \epsilon_{czmt} \tag{1}$$

Here Y_{czmt} is the logged average housing price for zip code z within county c in month m at year t. We control for time-varying zip code-level characteristics in $\mathbf{X}_{zmt}$, which are 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. We include these as baseline controls, but our results are robust to these baseline controls, which is not surprising given that the HTF is a plausibly random event.

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. θ_{ct} accounts for county specific shocks in a given year, for instance, local housing market shocks during the pandemic. θ_m accounts for seasonality. The key independent variable is the measure of the HTF exposure F_{zmt}, which is the number of days with HTF in the past 12 months for a zip code z at time mt. β captures the impact of being exposed to an additional day of HTF on the housing price.

Table 3.1 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 average housing price by 0.08%. Given that the average number of days with HTF in the sample is 5.5, the estimated coefficient suggests a 0.43% or a $1,958 reduction in the housing prices (evaluated at the average price $454,346). In column (2), we exclude baseline controls and find that the point estimate is robust to the inclusion of baseline controls although there is a slight uptick in the standard error because they absorb residual variations. In column (3), we test an alternative specification. In particular, we include year fixed effect rather than year by county fixed effect and find that the estimated effect is almost twice as large (in magnitude). This can happen when county specific shocks are correlated with the HTF occurrence. One possible scenario is a correlation between COVID in the large metropolitan areas such as NYC that has incurred larger adjustment in the housing price and frequent HTF occurrence along the Northeast coastal line. Comparison between columns (1) and (3) illustrate the importance of using a more stringent fixed effect model.

The small effect size we find is consistent with Murfin and Spiegel (2020), who find that relative SLR does not lower the housing price. This contrasts Baldauf et al. (2020) and Bernstein et al. (2019), which have found that SLR reduces the price of affected properties by 3–7%.[12] The differ-

[12] Related, but with somewhat different emphasis is Giglio et al. (2021), which study on the impact of the SLR risk *awareness* on the housing price. They find that a doubling in the share of listings that mention climate risk–related words is associated with a 2.4% decline in the transaction prices of properties in the high flood zone.

Table 3.1: Effect of High-Tide Flooding on the Housing Market

	(1)	(2)	(3)	(4)
N of Days with HTF (Past 12 Months)	-0.0008**	-0.0008**	-0.0015**	-0.0023***
	(0.0002)	(0.0003)	(0.0005)	(0.0004)
Dep.Var:	Log (Price)	Log (Price)	Log (Price)	Log (Rent)
Controls:	Yes	No	Yes	Yes
Fixed-Effects:				
Zip Code	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Year by County	Yes	Yes	No	Yes
Distance to Coast	Yes	Yes	Yes	Yes
Year	No	No	Yes	No
Observations	170,707	170,707	170,707	170,982

Note:
This table presents the effect of HTF on the transaction price (columns (1)-(3)) and rental rates (column (4)) based on equation (1) for zip codes overlapping with the NOAA inundation map. Column (4) is reproduced from Lee et al. (2023). All outcome variables are in log scale and baseline controls (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) are included in all columns except for column (2). Standard errors are clustered at the county level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

ence in the effect size could reflect the different source of variation. Namely, while Baldauf et al. (2020) and Bernstein et al. (2019) leverages cross-sectional variation in the SLR (practically, whether six feet or less of SLR would put the property underwater) across different spaces, we exploit both temporal and spatial variations in the HTF occurrence, which, in addition to adding temporal variations, translates a rather abstract concept into a hands-on and highly salient experience. Similarly, Murfin and Spiegel (2020) utilizes relative SLR, which is still cross-sectional but presumably better at controlling omitted factors by using the difference in SLR and land elevation change, and find null effect.

In column (4), we present the impact of HTF on the rental rates, which is reproduced from Lee et al. (2023) using the identical specification as equation (1). Importantly, the effect size is almost three times larger than our preferred specification in column (1), suggesting that current rental price change due to HTF is not fully capitalized into the housing price. This is surprising because one might easily expect that the impact on the housing price is likely to be *larger* than the impact on the rental rates because of (1) loss in the current use value and (2) higher subjective probability of disaster in the future.

Conceptual Framework. To explore why the change in the housing price is even smaller than the change in the rental rate, we consider a simple state-dependent Gordon growth model (Campbell and Shiller 1988, Campbell et al. 2009). We posit a two-period model as equation (2) where the housing price P in time t is determined by the concurrent and future rental rates, where future reward is discounted by δ.[13] The central feature of this model is that the rent R_t is state dependent where the "No Disaster" state denotes a disaster (such as hurricane)–free state and θ is the subjective probability of disaster. Reflecting the non-destructive nature of the HTF, a day is considered to be in the "No Disaster (ND) State" even if it is exposed to the HTF.

$$P_t = \theta R_t^D + (1-\theta)R_t^{ND} + \delta[\theta R_{t+1}^D + (1-\theta)R_{t+1}^{ND}] \tag{2}$$

How does HTF affect the housing price and rental rates? To see this, we can totally differentiate equation (2) with respect to HTF (F). Because HTF incurs inconvenience, it lowers rental rates in the ND state ($\frac{dR^{ND}}{dF} < 0$), but it does not impact rental rates in the disaster state ($\frac{dR^D}{dF} = 0$). Also, it makes flood risk more salient and delivers information on the likelihood of disaster ($\frac{d\theta}{dF} > 0$). Then, the impact of the HTF on the housing price can be expressed as (3).

$$\frac{dP_t}{dF} = \frac{d\theta}{dF}[(R_t^D - R_t^{ND}) + \delta(R_{t+1}^D - R_{t+1}^{ND})] + (1-\theta)[\frac{dR_t^{ND}}{dF} + \delta\frac{dR_{t+1}^{ND}}{dF}] \tag{3}$$

Because $\frac{d\theta}{dF} > 0$ and $R_t^D - R_t^{ND} < 0$, the first term is always negative. Similarly, $\frac{dR^{ND}}{dF} < 0$ and thus the second term is always negative as well, which collectively implies that $\frac{dP_t}{dF} < 0$. Further, equation (3) implies that the impact of the HTF on the housing price comes from two separate sources: increased disaster awareness ($\frac{d\theta}{dF}$) and lower rents in no-disaster state ($\frac{dR_t^{ND}}{dF} + \delta\frac{dR_{t+1}^{ND}}{dF}$) due to disruptions in daily lives from HTF (Lee et al. 2023).

Equation (3) provides useful insights as to the expected relationship between the rental rates and

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

the housing prices. First, suppose that $\frac{d\theta}{dF} = 0$ such that $\frac{dP_t}{dF} = (1-\theta)[\frac{dR_t^{ND}}{dF} + \delta\frac{dR_{t+1}^{ND}}{dF}]$. Then, $\frac{dP_t}{dF}$ is essentially determined by the present and future rental rates in the ND state. If the market believes that $\frac{dR_t^{ND}}{dF} \approx \frac{dR_{t+1}^{ND}}{dF}$ and reasonably forward looking (δ not too small), then the expression suggests that the impact of HTF on the housing price should be about the same as the impact of HTF on the current and future rents unless θ is very high.

Second, if we allow $\frac{d\theta}{dF}$ to be meaningfully large, then the impact of HTF on the housing price can be much larger than the impact of HTF on the rental rates.[14] The intuition is that now the market worries not only about lower rental rates in ND state due to the inconvenience caused by HTF, but also worries about experiencing more frequent D state (e.g., more often hurricane) where rental rate is $R^D < R^{ND}$.

Given the findings from Table 3.1 that only a fraction of rental rate change is capitalized into the housing price, the model provides two testable predictions: (1) $\frac{d\theta}{dF}$ should be small and (2) people's expectation about the future rental rate is optimistic, which can happen if people expect government interventions to mitigate the impact of SLR (Kelly and Molina 2023).

4 Impact of HTF on Climate Opinions

In this section, we empirically test the two empirical predictions derived from equation (3) using Yale Climate Change Opinion Maps (YCOM) data. Specifically, we estimate equation (4), which is a modified version of equation (1) reflecting the difference in the level of observation due to the difference in the spatial granularity between the housing price and climate opinion dataset.

$$log(Y_{ct}) = \beta F_{ct} + \gamma \mathbf{X}_{ct} + \alpha_c + \theta_t + \epsilon_{ct} \tag{4}$$

Here Y_{ct} is the logged survey response outcome (the fraction of population who said "Yes" to each question) for various questions for county c at year t. Our baseline control variables that account for time-varying county-level characteristics are in $\mathbf{X}_{ct}$, which are the number of days with moderate or major flood events in the past 12 months, the fraction of population with college degree, the fraction

[14] Another implicit condition is that $R^D - R^{ND}$ is large enough, but this is likely to be the case in reality for various reasons. For instance, finding a tenant after major disaster can be difficult, existing tenants are more likely to default, or a property might not be in a condition to accept tenants.

of minority populations, median income, and the fraction of rental units.

We also include county (α_c) and year (θ_t) fixed effects. The key independent variable is the measure of the HTF exposure F_{ct}, which is the number of days with HTF in the past 12 months for a county c at year t. β captures the impact of being exposed to an additional day of HTF on survey responses.

Figure 4.1 summarizes the estimated coefficients for six different questions grouped into three different categories that capture (1) exposure to climate related information, (2) climate risk perceptions, and (3) policy preferences.[15] The y-axis shows the impact of HTF on each survey responses ($\hat{\beta}$ from equation (4)) multiplied by the average number of HTF in the past 12 months (6.8).

For the exposure to information, we leverage the estimated percentage of population "who hear about global warming in the media at least weekly" and "who discuss global warming occasionally or often with friends and family". The estimated coefficients for coastal states, which are directly impacted by the HTF, show that there is a disproportionately large increase in the fraction of people who discuss about climate change in comparison to the increase in media exposure. This is in a stark contrast to the inland states where the effect on media coverage is much larger than the discussion. The contrast suggests that population in coastal states were already exposed to much climate change related news, but HTF sparks more active discussion among residents presumably it imposes a direct threat to their daily lives. In contrast, inland residents do not talk about this phenomenon as much as their coastal states peers presumably because SLR is not directly impacting them.

Next, we explore the impact of HTF on climate risk perceptions, which corresponds to θ from equation (2). We focus on responses to two questions which are the estimated percentage of people "who think that global warming is happening" and "who are somewhat/very worried about global warming". Surprisingly, despite higher exposure to media coverage and discussion, it does not seem to change perceptions about climate change. Specifically, for coastal states, the fraction of population who believe climate change is happening does not seem to change at all (cannot reject the null) and the fraction of people who are worried about climate change show very small increase. The effect from the inland state is smaller for both questions, which is plausible given that they are not affected by SLR. Importantly, this is consistent with a theoretical prediction: namely, a small $\frac{d\theta}{dF}$.

[15] Appendix Table A.1 presents the estimated coefficients.

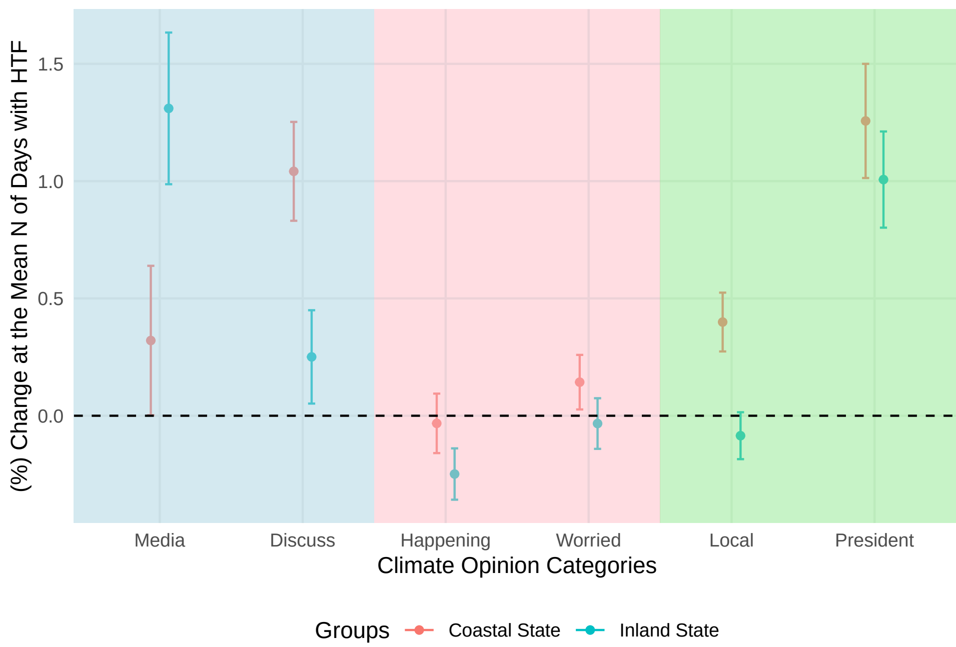


Figure 4.1: The Impact of HTF on Climate Change Related Opinions.

Finally, we investigate the impact of HTF on policy preferences, which is critically related to the future rental rate expectation.[16] For instance, Kelly and Molina (2023) finds that there are 162 adaptation infrastructure in place in Miami-Dade county in FL alone, and these projects increase property values about 5%. To test if policy preferences are impacted by HTF, we estimate equation (4) on two outcome variables which are the estimated percentage of population "who think their local officials should be doing more/much more to address global warming" and "who think the President themselves should be doing more/much more to address global warming". The estimated coefficients suggest that residents in the coastal states have a strong opinion about government intervention. For instance, there is a 1.3% increase in the proportion of population who think the president should take more responsibility in fighting climate change. Interestingly, people tends to think that climate change issues should be addressed at the federal government level although the benefit of adaptive infrastructure is very local. Also, similar to the estimates from other two categories, policy preferences of the inland state residents are much weaker than the coastal state residents.

[16]Ideally, we would like to directly observe "expectation" rather than "preference" for government intervention, because the former more directly predicts people's expectation about future rents. While the Yale survey does not ask people about their expectations on policy, policy preferences typically affect voting outcomes as is the case for carbon tax vote in Washington state (Anderson et al. 2023). Thus preference should be a useful proxy for expectations on future policy responses.

Table 4.1: Effect of High-Tide Flooding on the Housing Price by Climate Opinion

	(1)	(2)
N of Days with HTF (Past 12 Months)	-0.0013***	-8.83e-5
	(0.0003)	(0.0002)
Sample:	Weak Opinion on Gov Intervention	Strong Opinion on Gov Intervention
Fixed-Effects:		
Zip Code	Yes	Yes
Year by County	Yes	Yes
Month	Yes	Yes
Distance to Coast	Yes	Yes
Observations	97,092	73,615

Note:
This table presents the effect of HTF on the transaction price for states with stronger (column (1)) and weaker (column (2)) opinions about government intervention, respectively. All outcome variables are in log scale and baseline controls (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) are included in all columns. Standard errors are clustered at the county level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

In Table 4.1, we directly investigate whether the difference in opinion about policy can explain the difference in capitalization. For this exercise, we first classify coastal states depending on the estimated impact of HTF on opinion for government intervention. In practice, a state is classified as strong opinion group if $\hat{\beta} > 0$ (where $\hat{\beta}$ is from equation (4) for both "local official" and "president" questions.[17] The effect we find is striking: while states that have weaker preference about government intervention experiences 0.13% reduction in the housing price with one additional day with HTF, which is much larger than 0.08% for the entire sample, states in the strong preference states essentially have null effect. This suggests that even a highly vivid and salient manifestation of SLR fails to affect the housing market when people expect government to step in. Importantly, this finding empirically supports the model prediction that an optimistic view about future rental flow hinders housing price adjustments.

[17] We choose 0 because as Appendix Figure A.2 shows, 0 naturally splits the states into 9 (low opinion group) and 12 (high opinion group).

5 Conclusion

Despite existential threats imposed by SLR, existing evidence on the impact of SLR on the housing price in the coastal communities is mixed partly because of identification challenges. This paper leverages a novel source of variation in the SLR manifestation—high tide flooding—to test whether the market adequately prices SLR risk and explore potential explanations.

Using zip code level housing price data, we find that being exposed to one additional day of HTF reduces housing prices by 0.08%. We report that the magnitude is about 1/3 of the impact of HTF on the rental rates from Lee et al. (2023), and construct a model that guides us to empirically test potential mechanisms. The model predicts that the manifestation of SLR risk, namely HTF, might have limited impact on the housing prices when (1) HTF has little impact on the people's expectation about future disaster probability and/or (2) people are optimistic about future rental rates due to, for instance, mitigation investments by the government. We estimate the impact of HTF on climate beliefs and opinions to find that results that are consistent with these theoretical predictions. The findings of this paper underscore the risk of policy-induced moral hazard.

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A Additional Tables and Figures

Table A.1: Effect of High-Tide Flooding on Climate Opinions

	(1)	(2)	(3)	(4)
Panel A: Exposure to Climate Change Information				
N of Days with HTF	0.0005*	0.0016***	0.0020***	0.0004*
	(0.0003)	(0.0002)	(0.0003)	(0.0002)
Dep.Var:	Log (Media)	Log (Discuss)	Log (Media)	Log (Discuss)
Sample:	Coastal	Coastal	Inland	Inland
Observations	4,972	4,972	7,271	7,271
Panel B: Perception on Climate Change				
N of Days with HTF	-5.04e-5	0.0002*	-0.0004***	-5.16e-5
	(0.0001)	(9.21e-5)	(8.66e-5)	(8.55e-5)
Dep.Var:	Log (Happen)	Log (Worried)	Log (Happen)	Log (Worried)
Sample:	Coastal	Coastal	Inland	Inland
Observations	4,972	4,972	7,271	7,271
Panel C: Climate Policy Preference				
N of Days with HTF	0.0006***	0.0019***	-0.0001	0.0016***
	(9.93e-5)	(0.0002)	(7.92e-5)	(0.0002)
Dep.Var:	Log (Local)	Log (President)	Log (Local)	Log (President)
Sample:	Coastal	Coastal	Inland	Inland
Fixed-Effects:				
County	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	4,972	3,705	7,271	5,398

Note:
This table presents the effect of HTF on various climate opinions estimated based on equation (4). Each panel presents results for exposure to climate change information (Panel A), perception on climate change (Panel B), and climate policy preference (Panel C) for coastal state (columnns (1) and (2)) and inland states (columns (3) and (4)), respectively. All columns include baseline controls (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). Standard errors are clustered at the county level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

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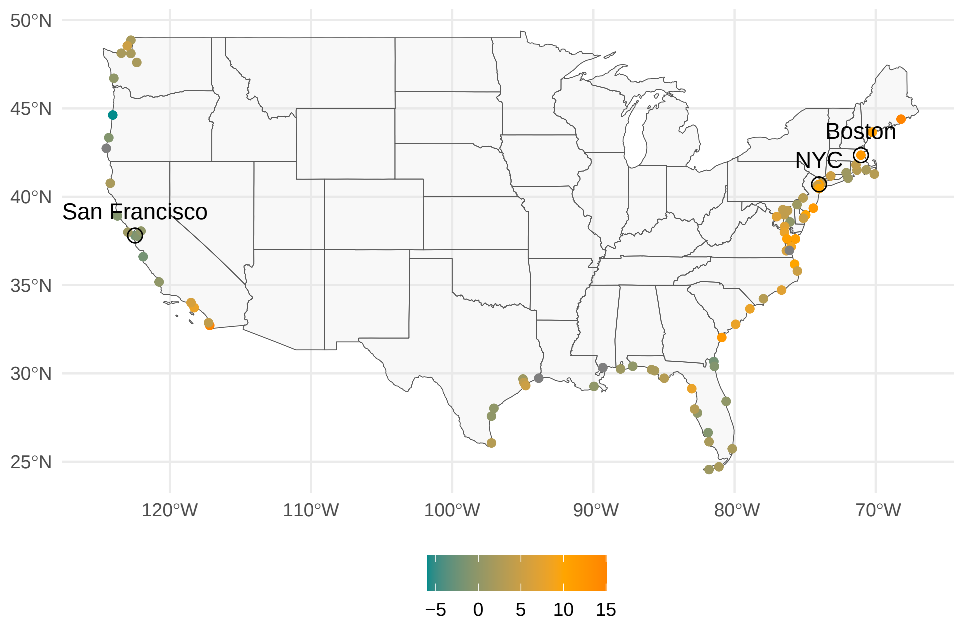

Figure A.1: Location of NOAA Gauge Stations and Change in the Number of Days with HTF between 2001 and 2022. This figure depicts 84 NOAA gauge stations within the contiguous US that has flood thresholds from Sweet et al. (2018). The color illustrates the change in the number of days with HTF between 2001 and 2022 for each site

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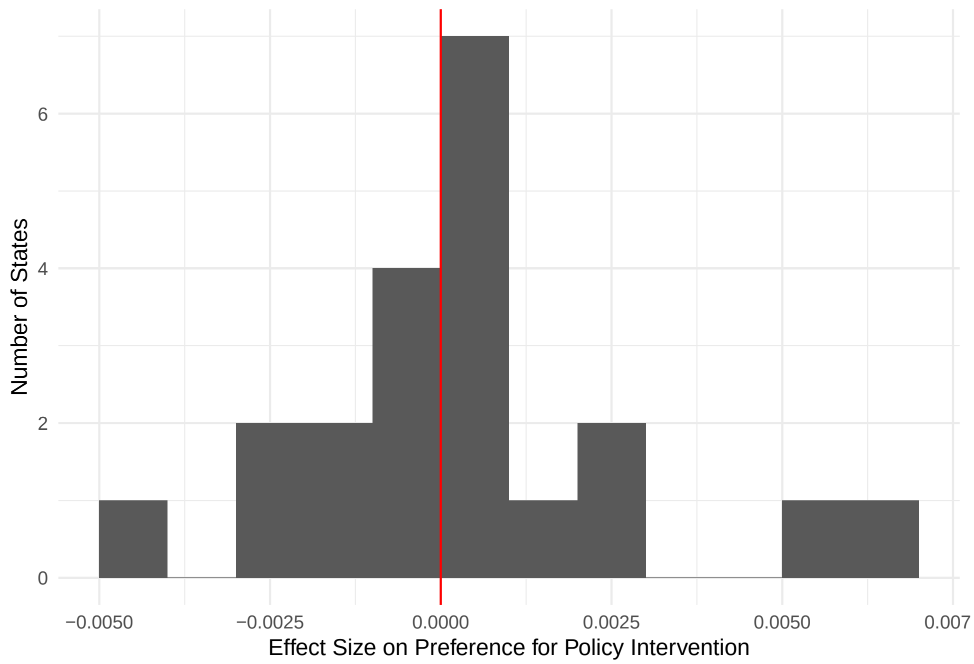

Figure A.2: The Distribution of the Impact of HTF on Opinion about the Policy Intervention. The histogram shows the distribution of the state-specific impact of HTF on preference for policy intervention.

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