Estimating the Indirect Cost of Floods: Evidence from High-Tide Flooding

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Abstract

While a theoretically consistent cost of flooding is a welfare loss from the event, most existing estimates are based on direct and insured damage because of measurement challenges. In this paper, we leverage temporal and spatial variations in the occurrence of High-tide flooding (HTF), highly disruptive, yet rarely destructive small scale coastal flooding, to estimate the indirect cost of flooding. Our analysis reveals that HTF significantly disrupts daily lives, resulting in a 9.0% reduction in the number of trips on the day of HTF. Further, we show that exposure to one additional day of HTF in the past 12 months reduces rental rates by 0.23%, indicating that a lower bound indirect cost of flood is $45 per day. Our findings suggest that omitting disutility from floods underestimates the true cost of floods by 28%.

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1 Introduction

During the tidal floods, which can happen several days each month, "you can't have parties, you can't have get-togethers, and you can't have friends over," says Dunker, whose street in Hamilton Beach has been repeatedly cut off by floodwaters since she moved in 23 years ago. "One year, it was flooded from Thanksgiving to Christmas. We didn't get a holiday that year. That's how it is. You've got to live with it." (Curbed New York, Oct 12, 2017)

While floods have become more extreme in both intensity and frequency due to climate change, most prior works studying the economic consequence of floods have focused on catastrophic events such as hurricanes (Strobl 2011, Cavallo et al. 2013, Gallagher 2014, Hsiang and Jina 2014, Deryugina et al. 2018, Deryugina and Molitor 2020). However, with the sea level rise, the frequency of small-scale, rarely destructive, yet highly disruptive high tide flooding (HTF)—is rapidly increasing along the coastal neighborhoods in the US (Sweet 2018, Taherkhani et al. 2020). 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 per year in the next 10–15 years (Thompson et al. 2021). Despite their preponderance, and unique physical characteristics that allow researchers to estimate otherwise intricate economic parameters, HTF has received disproportionately small attention.

However, understanding how HTF shape our daily lives and housing market is important for at least two reasons. First, while a theoretically consistent cost of flooding is a welfare loss from the event that encompasses both direct and indirect costs, most earlier studies on flood cost estimation considered only direct damage because of measurement challenges (Gall et al. 2011, Kousky 2014). HTF provides a unique opportunity to estimate the "indirect cost" of flood using the hedonic approach because it substantially disrupts daily lives but rarely incurs direct damage on material assets.[1] Second, given its current and expected prevalence and ruinous impact, understanding the impact of HTF is of first-order importance in its own right.

In this paper, we provide one of the first empirical evidence on the impact of HTF on mobility and rental rates. For this, we collect daily water level records for the past 20 years from 84 NOAA gauge

[1] Examples of indirect costs are business interruption, adaptation costs, loss of use value, mortality and injury, and environmental degradation (Kousky 2014).

stations in the coastal states of the contiguous US and compare them with the site-specific flood thresholds to construct historical HTF occurrence data. We link this with zip code level monthly rental rates data from Zillow (2015-2021) and daily points of interests (POI) visits data from Safegraph (2018-2021). We also utilize the HTF inundation map from NOAA to identify areas that are affected by HTF. Plausibly exogenous temporal and spatial variations in the HTF occurrence form the basis of our identification.

We start our empirical exercise by providing direct evidence that illustrates how HTF disrupts everyday lives. Specifically, building on the earlier works that have documented the negative impact of HTF on road conditions (Hino et al. 2019, Hauer et al. 2021), we focus on how HTFs affect mobility, namely the number of visits to various non-work POIs. For this exercise, we first aggregate the POI level daily number of visit counts to the zip code level, and compare a day with and without HTF within the same zip code after controlling for the day of the week, seasonality, and county-year specific shocks. We find that on a day with HTF, the number of visits per store decreases by 9.0%. One immediate concern is that this estimate might simply capture various substitution behaviors such as intertemporal substitution or stockpiling behavior (purchasing more per store visit), which could exaggerate the "true" magnitude of disruption. By estimating (1) category-specific (restaurants, retail stores, and entertainment venues) HTF effect and (2) HTF effect by event time, we show that substitution behavior is not pronounced.

Next, we turn our attention to the impact of the HTFs on the rental rates, where we compare zip codes that have experienced a large versus small change in the HTF exposure over time after accounting for differences in the baseline exposure. Specifically, we find that having one additional day of HTF in the past 12 months reduces the average rent of affected zip codes by 0.23% or $45 at the mean annual rental rate. Further, at mean annual number of days with HTFs (5.5), this translates into a 1.3% (or $240) lower rental rate per year. Importantly, the impact of HTF on rent is larger for states that had larger impact of HTF on the number of visits, which implies that impaired mobility is an important source of disutility from floods. Moreover, we estimate a rent–distance gradient and find that the negative impact of HTF is monotonically decreasing as a property gets farther away from the coastal line, and becomes indistinguishable from zero beyond 40 miles. Finally, the impact is similar between zip codes with high versus low levels of climate change beliefs, which is plausible given that the physical impact of the HTF today is not contingent on the level of belief about the future.

Building on the hedonic model, we interpret the estimated impact of HTF on rent as willingness-to-pay (WTP) to avoid disutility from floods, which is distinguished from direct damage on assets. Such an interpretation builds on the fact that HTFs rarely incur direct damage, but disrupt daily lives. Armed with this parameter, we calculate two welfare estimates: indirect costs from the Presidential Disaster Declaration (PDD) floods, which can be considered as "large" floods and welfare loss due to the HTF. For the first exercise, we take the average MWTP $45 and multiply it by the number of households living in a county exposed to the PDD floods and by each events' duration. The resulting annual welfare cost is as large as $9 billion over the 2018–2021 period, which is 28% of estimated direct cost of floods in the US ($32.1 billion) (Wing et al. 2022). Although this figure is already substantial, we believe this number is likely to be a lower bound because (1) inconvenience from large floods such as PDD floods would be much larger than inconvenience from the HTF and (2) households exposed to smaller than PDD floods are excluded from this calculation.

For the second welfare exercise, we take the estimated effect (0.23%) and multiply this with zip code-specific rental rates and the number of days with HTF. We find that over the 2015–2021 period, welfare loss due to the HTF in the coastal communities in a given year is $6 billion. Note, this number is also likely to be a lower bound because we excluded zip codes that are overlapping with the inundation map but not included in the Zillow rental data.[2] Further, with an exponential increase in the days with HTF due to the sea level rise, this number can grow as large as $29 billion in 2030, although this estimate should be taken with a caveat because of the likely shift of the hedonic price schedule over time.

This paper contributes to three different strands of literature. First, it is related to earlier works estimating the cost of natural disasters (Nordhaus 2010, Mendelsohn et al. 2011, Strobl 2011, Cavallo et al. 2013, Smith and Katz 2013, Hsiang and Jina 2014, Desmet et al. 2021, Burzyński et al. 2022). These works rely on either macroeconomic outcomes such as GDP or damage on physical assets to measure the cost of natural disasters. This paper provides the first estimate of the indirect

[2] Zip codes with infrequent transactions are excluded from Zillow rental data.

cost of floods by connecting a novel identification strategy to the hedonic framework, which is an important step toward a more comprehensive micro-founded cost estimate. The findings suggest that ignoring indirect cost, which is at least $9 billion per year, could lead to a substantial underestimation of the true cost of floods.

Second, it complements nascent literature studying the impact of HTFs on daily lives (Hino et al. 2019, Hauer et al. 2021, Griggs and Reguero 2021, Hague et al. 2022). We produce the first empirical evidence on how the HTF affects mobility and a rental market, and presumably more importantly, provide a welfare cost estimate. The findings indicate that HTF seriously threatens the quality of life in coastal communities, incurring a substantial economic costs.

Finally, this paper builds upon recent studies that have utilized highly frequent and geographically detailed mobile phone data to assess spatial mobility patterns (Miyauchi et al. 2021, Athey et al. 2021, Abbiasov et al. 2022, Kreindler and Miyauchi 2023). Specifically, our approach is similar to those that have used mobile phone-based visit records to estimate the impact of the pandemic and related policy responses (Goolsbee and Syverson 2021, Couture et al. 2022). The findings of our research suggest that cellphone data can be valuable for promptly detecting natural disasters, thereby significantly improving the effectiveness of disaster responses (Yu et al. 2018).

This paper proceeds as follows. Section 2 provides background information on the HTF, details the data sources, and provides summary statistics. Section 3 analyzes the impact of HTF occurrence on mobility, and Section 4 studies the impact of HTF on rental rates. Section 5 discusses welfare implications. Section 6 concludes.

2 Background and Data

2.1 High-Tide Flooding

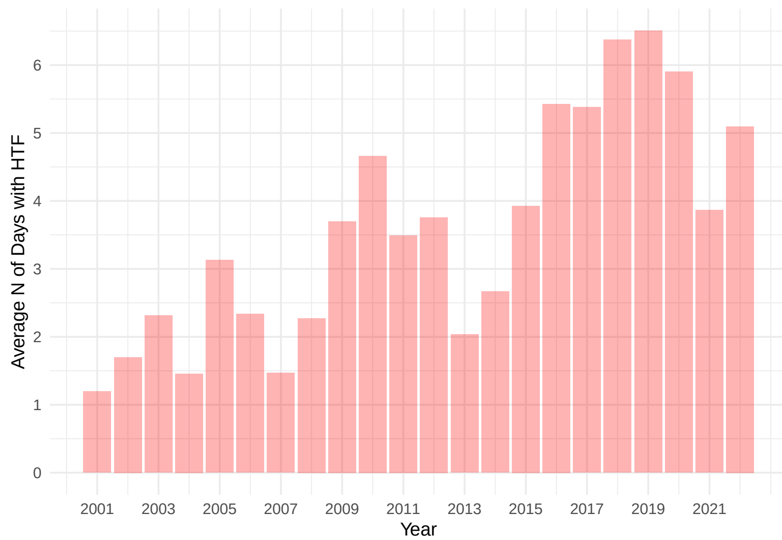
Trend. High-tide flooding (HTF)—also known as sunny day flooding, nuisance flooding, or recurrent tidal flooding—is a temporary inundation of low-lying areas during exceptionally high tide events. While the tidal movement is not new, HTF has become more prevalent in recent years due to sea level rise. As a result, the average number of days with HTF in the contiguous US has more than tripled in the past two decades (Figure 2.1 (a)).

Despite the overall increasing trend, as Appendix Figure A.1 and A.2 illustrates, the number of days with HTF has increased disproportionately higher along the Atlantic Coast than the Pacific Coast. Such regional differences are a product of two factors (Sweet 2018): (1) storm surge potentials are lower in the West Coast because of milder weather and bathymetric conditions; (2) over the last several decades, sea level rise has been slower in the Pacific Coast. Further, HTF frequency is most prevalent over fall to winter because of the alignment of earth and moon (Sweet 2018). These rich natural variations forms the basis of our identification strategy.

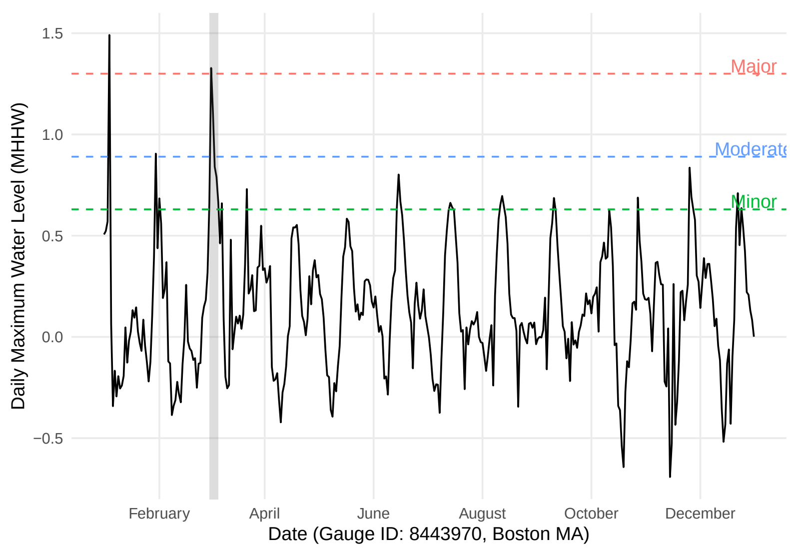
Measurement. NOAA defines HTF as an event where water level falls between minor and moderate flood thresholds (Sweet 2018). To illustrate this, in Figure 2.1 (b), we overlay daily maximum water height for 2018 from a gauge station in Boston. A few points are worth noting. First, the graph clearly shows that the HTF pattern is in sync with the moon phases, which is consistent with the physics behind the phenomenon (i.e., a product of tidal movement). Second, water levels can exceed the minor threshold as a precursor to or a descendant of a larger flood event. For instance, the water level in the highlighted period (March 4, 2018) in Figure 2.1 (b) is between the minor and moderate threshold, so it should be counted as HTF. However, this is not a "true" HTF that incurs minimal direct damage because it is preceded by a major flood on March 2. In defining HTF, we exclude these cases because of potential direct damage incurred by preceding or following larger floods—practically, we use a $\pm$ 3-days window. Further, we separately document dates with water level higher than "moderate" or "major" thresholds to control for the impact of large flood events.

Impact. Anecdotal evidence suggests that HTF seriously disrupts daily lives. For instance, people give up outdoor exercise, dog walk, or restaurant gatherings; wade through brackish water for half-mile to get to their cars, which causes skin rashes (Flechas and Staletovich 2015, Alvarez and Robles 2016, Kensinger 2017, Mazzei 2019). Further, the impact can go much farther than the inundation area—for instance, areas experiencing the sharpest increase in traffic congestion do not necessarily coincide with inundation areas (Hauer et al. 2021), which reflects people's choices on alternative routes.

Reflecting the physical characteristics of the phenomenon, HTF rarely causes direct damage. Fig-



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

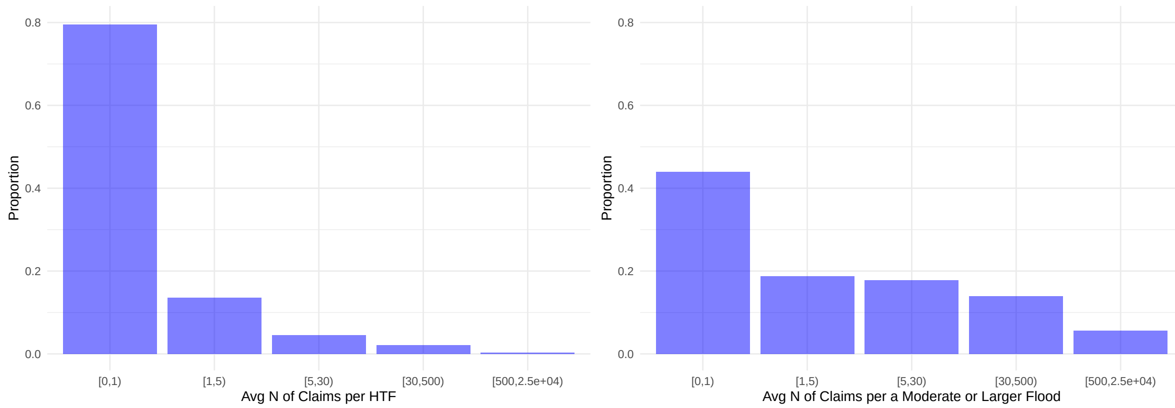


(b) Detecting HTF using Water Levels Data

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

ure 2.2 shows this point by illustrating the number of the National Flood Insurance Program (NFIP) claims per community given flood occurrence for different flood sizes. In Panel (a), which is for HTFs, we show that for only 7% of day-community pairs, the number of claims are higher than 5.[3] This is a stark contrast to floods that are moderate or larger (Panel (b)), which shows that in 37% of

[3]The number of claims can be positive for HTFs as well for at least two reasons. First is a measurement issue. Because HTF "occurs" whenever water level falls between minor and moderate flood threshold, there are HTFs that are closer to "moderate" sized flood. Indeed, when we define HTF as floods that fall under minor and $\frac{\text{Minor+Moderate}}{2}$ threshold, the number of day-community pairs with claims higher than 5 reduces to 5.8%. Second, anecdotes report that HTF floods basements (Kensinger 2017).



(a) Average N of Claims for HTF (Minor Floods)   (b) Average N of Claims for Moderate or Major Floods

Figure 2.2: Average Number of the National Flood Insurance Program (NFIP) Claims for Different Flood Sizes. Panels (a) and (b) show how the average number of NFIP claims from each NFIP community differ by flood size between 2001 and 2019.

cases, the number of claims are higher than 5.

With 20+ days of days with HTF, the cost is already non-trivial, but, unfortunately, this magnitude is a tiny fraction of what is expected to happen in the near future. With rising sea level, many cities along the Atlantic Coast are expected to have 50+ days with HTF in a given year by 2030 (Thompson et al. 2021). The disutility from such a prolonged inundation could be exponentially larger than the current level.

2.2 Data Description

To understand the impact of HTF on daily lives and resulting rental rates, we collect and combine three different sets of data.

Rental Rates. We use Zillow Observed Rent Index (ZORI), which is quality-adjusted monthly asking rents averaged over the 35th to 65th percentile range for all homes and apartments in a given region.[4] It adjusts for the likelihood of units being listed to represent rental rates across the entire market, not just those homes 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 re-

[4]For more detail, see https://www.zillow.com/research/methodology-zori-repeat-rent-27092/ (accessed on Mar 2, 2023).

strict our sample to the zip codes within the 21 coastal states in the contiguous US.[5]

Water levels. We construct coastal flood history data using the NOAA water levels data from 84 gauge stations in the coastal states of the contiguous US (See Appendix Figure A.1 for gauge station locations). We retrieve verified daily high water level data for each gauge station using R package "rnoaa".[6] Then, for each station, we compare time series of water height to the flood thresholds from Sweet (2018), which is objective and nationally consistent set of minor, moderate, and major coastal flooding thresholds.

Mobility. To explore the HTF's impact on mobility, we use trip counts data from Safegraph. The data documents daily number of visits to 12 million points of interest (POIs) from 45 million smartphone users in the US for 2018–2021.[7] It also provides the coordinate of each POI, its category based on the North American Industry Classification System (NAICS) code. In Appendix Table A.1 we summarize the total number of POIs and corresponding visit counts by the NAICS code. The table shows that the vast majority of destinations captured by Safegraph data is non-work related POIs such as retail stores, restaurants, entertainment and health care.[8] These POIs are everyday destinations with frequent visits, which is useful to detect any anomaly in the number of visits caused by HTF.[9]

2.3 Summary Statistics

In Figure 2.3, we show the overall number of visits during our sample period. One immediate observation from Panel (a), which shows the raw data trend, is that the overall number of trips fluctuates a lot. This is at least partly driven by the fact that the number of cellphone devices used for data collection has increased over time (Kurmann and Lalé 2022). To account for this, we divide the daily

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

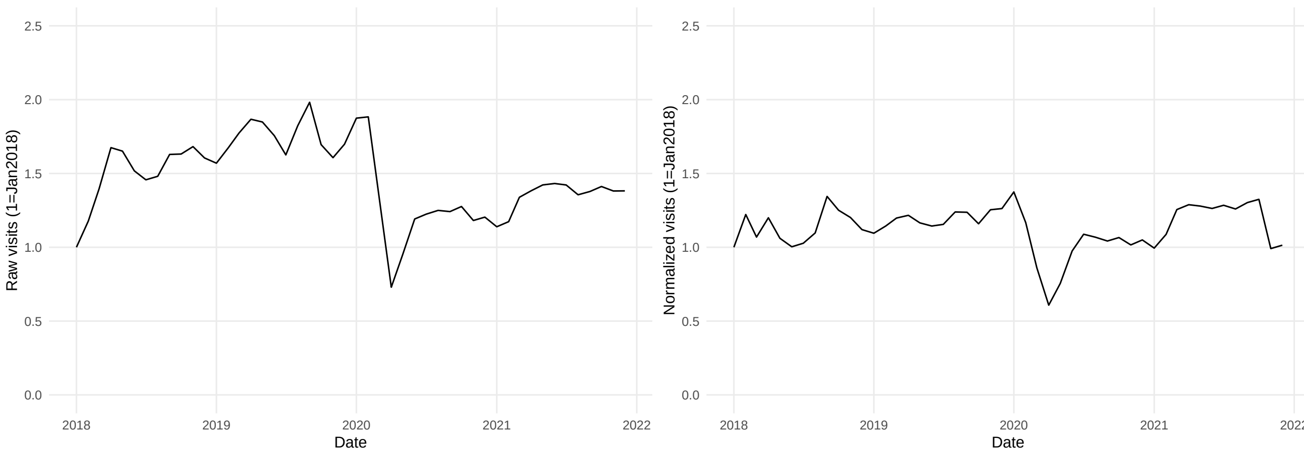
[7]See https://docs.safegraph.com/docs for more details (accessed on Jun 15, 2023).

[8]Indeed the top three categories we separately analyzed in Table 3.1, make up 55% of the POIs and account for 66% of the trips in our sample.

[9]One concern about cell phone data is the potential for location error. The mobile GPS positioning can only achieve an accuracy of roughly 5 meters. When the cell phone device is in dense urban clusters, the app-based GPS positioning might not be able to distinguish whether a user is in one store or another. Another caveat is the data do not cover all actual visitors but rather a subset of users that have a smartphone and who have enabled their phone's GPS location feature in various apps. It could thus be under-representing visitors from demographic groups that have a lower proclivity to own or use a smartphone (e.g., elderly individuals and low-income residents).

Table 2.1: Summary Statistics for Key Variables

Variables	Min.	Max.	Mean	Std.Dev.	N
Rental Rates	132	391,867	19,243	10,881	172,364
% Inundated	0	89.72	3.51	8.23	172,364
Distance to the Coast (Miles)	0.018	113	12.65	14.95	172,364
N High Tide Floods (Per Year)	0	44	5.45	4.76	172,364
N Mod+Large Floods (Per Year)	0	11	0.46	0.983	172,364
Precipitation (Daily Average)	0	47.12	3.45	2.91	172,364



(a) Raw Visit Counts (b) Normalized Visit Counts

Figure 2.3: The figures show the standardized counts of total monthly raw and normalized visits to all Safegraph POIs in our samples. We standardized the visit counts using Jan 2018 as the base month. See text for more details.

number of visits to an average POI within a zip code by the number of cellphone devices at the corresponding month and zip code used by Safegraph following Kurmann and Lalé (2022).[10]. For instance, zip code 02138 has 1.2 visits per POI on Jan 1, 2018. We normalize this by dividing 1.2 by 10, which is the number of cellphone devices for the zip code 02138 in January of 2018. To further reduce measurement error, we restrict the data to zip codes which have at least 10 visits per week.[11] Figure 2.3 (b) depicts the normalized visit counts for all POIs, which is substantially smoother than Figure 2.3 (a).[12] Motivated by this, we use normalized visits for our analysis.[13]

[10]Given that Safegraph only provide information about the number of devices at the month and census block group level, we aggregate the number of devices to zip code level and then match with weekly-zip-code level visit data for normalization.

[11]In Section 3, we show that our results are robust to the choice of the threshold.

[12]Normalized dependent variable can also be viewed as the number of visits per device.

[13]A sharp drop in the number of visits in 2020 is due to the COVID pandemic.

Table 2.1 presents summary statistics for key variables used in the rental rate analysis. A few points are worth noting. First, an average annual rent for the zip codes that has any overlap with the inundation map—which is our primary sample—is $19,243 ($1,604 per month). This is nearly $5,000 higher than the average annual rent for all other zip codes in the Zillow rent dataset that are not overlapped with the inundation map.[14] The difference in the rental rates (at least partly) reflects amenity value of being closer to the ocean. The level difference in rental rates suggest that zip codes outside of the inundation map might not be a good control group. Thus our empirical analysis focuses on within inundation area variations.

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.

Third, an average number of HTF in the past 12 months from a given month is 5.5 over 2015–2021 period. While this is substantially higher than the start of the 2000s (Figure 2.1), the number is expected to grow exponentially over the next decades. For instance, many cities along the east coast are expected to experience 50+ days of HTF in a given year in just 10–15 years (Thompson et al. 2021). Not surprisingly, frequency of larger flood events are much lower. During the same period, moderate or major flood happened with a 1/10 frequency. We include the number of larger floods as a baseline control in our empirical analysis.

3 High Tide Flooding and Mobility Consequences

In this section, we provide evidence that establishes the "direct" or "first-stage" effect of the HTF. Building on the earlier findings on the detrimental impact of HTF on road/traffic conditions (Hino et al. 2019, Hauer et al. 2021), our exercise focuses on identifying the impact of HTF on mobility. For

[14] There are 7,042 zip codes in the Zillow rent dataset where 2,102 of them have positive overlap with the inundation map.

this, we estimate equation (1).

$$log(Visits_{zdt}) = \beta F_{zdt} + \gamma \mathbf{X}_{zdt} + \alpha_{zwm} + \theta_{ct} + \sum_{i=1}^{10} P_{izdt} + \epsilon_{zdt} \quad (1)$$

Here $log(Visits_{zdt})$ is logged average daily number of visits to a POI located in a zip code z in date d (e.g., Jan 1) at year t. F_{zdt} is a dummy variable that takes 1 when there is HTF for zdt. We control for time-varying zip code-level characteristics in X_{zdt}, which include moderate or larger flood event occurrence, the fraction of population with college degree, the fraction of minority populations, median income, and the fraction of rental units. We also control for the effects of precipitation ($\sum_{i=1}^{10} P_{izdt}$), where P_{izdt} is an indicator variable for daily precipitation bins. We include the zip code by day-of-the-week by month fixed effects, α_{zwm}, to control for a zip-code-specific seasonality as well as baseline differences by day (e.g., Monday vs. Saturday). We also include county by year fixed effects, θ_{ct}, to capture county specific shocks that might affect daily visits, such as the differential impact of pandemic across counties.

The coefficient of interest is β, the effect of HTF on the number of visits to an average POI. In addition to explore the overall effect (i.e., effect to the all POIs), we also estimate category specific effects for (1) accommodation and food, (2) retail trade, and (3) arts, recreation, and entertainment categories, which are the three most popular POI types.

We also fit an event study model using equation (2). Here we estimate day-by-day differences in the number of visits per POI 7 days before and after HTF.[15] The key independent variable is $D_{zpdt,\tau}$, which is a dummy variable that takes 1 if it is the τth day since the day of HTF event.

$$log(Visits_{zdt}) = \sum_{\tau \in [-7,7], \tau \neq -1} \beta_\tau D_{zdt,\tau} + \gamma \mathbf{X}_{zdt} + \alpha_{zwm} + \theta_{ct} + \sum_{i=1}^{10} P_{izdt} + \epsilon_{zdt} \quad (2)$$

Table 3.1 presents the impact of HTF on the average number of visits per POI. Column (1) shows that being exposed to HTF leads to a 9.0% ($e^{-0.094} - 1$) decrease in the number of visits per POI (for POI of all categories), suggesting that HTFs indeed incur substantial disruptions to mobility.

[15] We do find consecutive HTFs in our sample, however, these events only account for less than 5% of the HTF. Therefore, we exclude these events for our event study estimation.

Table 3.1: Effect of High-Tide Flooding on the Number of Visits

	(1)	(2)	(3)	(4)
HTF Event	-0.094***	-0.092***	-0.081***	-0.114***
	(0.007)	(0.007)	(0.007)	(0.008)
Types	All	Accommodation and Food	Retail Trade	Arts Entertainment and Recreation
Observations	3,054,951	3,041,802	3,052,029	3,049,107

Note:
This table presents the effect of HTF on normalized visits based on equation (1) for zip codes overlapping with the NOAA inundation map. All outcome variables are in log scale and all columns include baseline controls (moderate or larger flood event occurrence, the fraction of population with college degree, the fraction of minority populations, median income, the fraction of rental units, precipitation, county by year fixed effects, and zip code by day-of-week-of-month fixed effects). Column (1) shows the effect for all POIs whereas columns (2)-(4) are for three specific types of POIs. Standard errors are clustered at the county level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

It is important to note that a 9.0% reduction only captures the extensive margin effect, and thus underestimate the extent of disruptions. That is, while some people might still complete a trip by taking an alternative route or simply driving slowly, which increases the time cost, the estimate in column (1) does not capture such an effect.

One potential concern for column (1) is that it might capture an effect from various substitution margins, and thus overstating the true magnitude of disruption. For instance, similar to consumption responses to extreme temperatures reported in Lee and Zheng (2023), people might reduce the number of trips while maintaining consumption level by increasing the amount purchased per trip or simply switch the date of visit.[16] To explore these possibilities, we explore category specific treatment effect for three largest POI categories in columns (2)–(4). Importantly, because some POIs provide services that are easier to stockpile than others (e.g., products from retail stores are easier to store than products from entertainment service venues), we can test if a higher purchase per store visit might explain a 9.0% reduction. We find that the impact of HTF on the number of visits per POI are by and large similar across different types of POIs, which rules out the stockpiling margin.

[16]Another potential margin is spatial substitution. Namely, people might visit stores in unaffected areas. While this is plausible, we believe that the effect in column (1) is not likely to capture this effect because our HTF measure varies only at a large geographical scale (because NOAA gauge stations are sparsely located).

If anything, we find that the point estimates is smallest for the retail trade category.[17]

Further, event study graphs in Figure 3.1 suggest that there is no active intertemporal substitution. That is, we find a very sharp reduction in the number of visits per POI on the day of HTF, but there is no anticipatory or rebound effect either before or after the event. Such a pattern is consistently found for all POIs in panel (a) as well as for specific categories in panel (b)–(d). Taken together, the impact we find in column (1) in Table 3.1 does not seem to be driven by these margins of substitutions.[18]

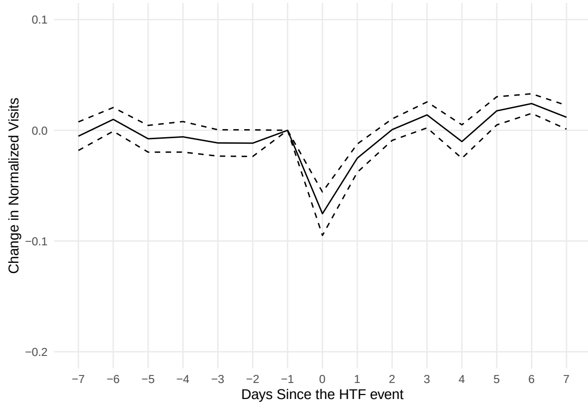
Finally, we leverage the impact of HTF on mobility to provide additional evidence on the nature of HTF. That is, while Figure 2.2 shows that the number of flood insurance claims are small for HTF, there might still be physical damage due to HTF, albeit too small to claim flood insurance. The number of visits to various repair shops after HTF can provide a useful insight to this regard. That is, if HTF causes direct damage on assets, people might visit auto repair shops, hardware stores, or electronics repair shops more often than usual.

Appendix Figure A.3 shows the result. Similar to other POIs in Figure 3.1, we find a sharp drop in the number of visits per POI on the day with HTF. Some POIs, in particular home and garden repair shops, show rebound in the post period, which suggests some damage incurred due to HTF. This is consistent with anecdotal evidence which find that HTF might flood basement, for instance. However, we also do note that the cumulative effect of HTF on the number of visits for home and garden repair shops are still negative at -29% ($e^{-0.34} - 1$).[19] This indicates that although there seems to be some increase in the number of visits to these repair shops, the magnitude seems small which is consistent with Figure 2.2 that HTF rarely incurs direct damage on assets.

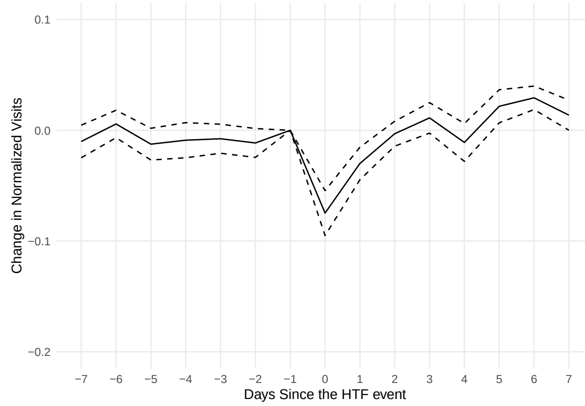
[17] Safegraph data has sales data for each POI, which potentially allow us to directly test a stockpiling behavior. However, this data is only available at the monthly level, which might substantially underestimate such a behavior that can happen at weekly or even daily level. Further, sales data is available for a subset of POIs, which may create a selection issue as well.

[18] Another robustness check for column (1) comes from Appendix Table A.2. As discussed in Section 2.3, we restrict the data to zip codes which have at least 10 visits per week. Appendix Table A.2 shows that the results are essentially identical even if we change the threshold.

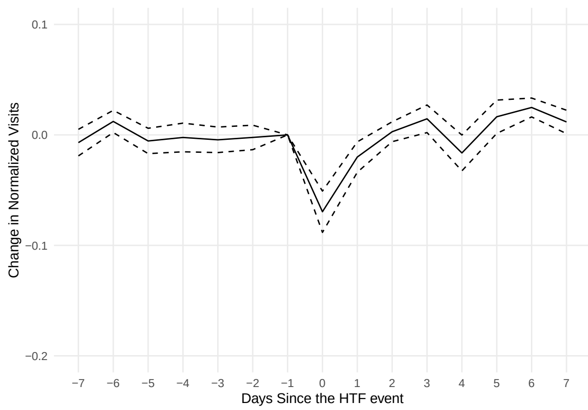
[19] 95% CI for the point estimate (-0.34) is -2.27 to 1.58.



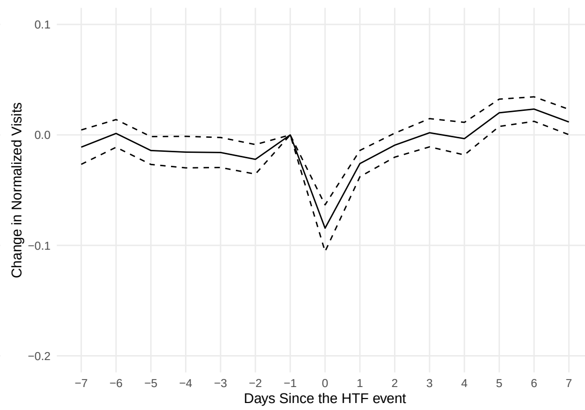
(a) All POIs



(b) Accommodation and Food Services



(c) Retail Trade



(d) Arts, Entertainment, and Recreation

Figure 3.1: The Effects of HTF on the Average Number of Daily Visits by Event Time. These plots show the HTF impact on the number of visits in event time (7 days before and after the HTF event). We control for moderate or larger flood event occurrence, the fraction of population with college degree, the fraction of minority populations, median income, the fraction of rental units, precipitation, county by year fixed effects, and zip code by day-of-week by month fixed effects.

4 Effect of High Tide Flooding on Rental Rates

To estimate the impact of HTF on rental rates, we estimate the regression model in equation (3) using zip codes that are overlapping with the inundation map.

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

Here Y_{czmt} is logged average monthly rent 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 also show that our estimates are robust to these control variables.

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 variables are 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 rent. We show that the estimated β is robust to alternative specifications.

Before further proceeding, it is worth noting the difference between two estimating equations for mobility and rent. For the mobility impact, we leveraged day to day HTF occurrence not only because mobility data is available at the daily level but also because the effect is sharp, and coarser temporal data might attenuate the contemporaneous effect due to potential intertemporal substitution. For the rental analysis, on the other hand, we leverage the differences in the number of HTF occurrences over the past 12 months because (1) there is likely to be a time lag between the date of event and rental rates adjustment and (2) the effect is likely to be cumulative.

Table 4.1 shows the impact of having HTF on rental rates. The estimated coefficient in column (1) indicates that being exposed to one additional day of HTF within the past 12 months reduces average rent by 0.23%. Given that the average number of days with HTF in the sample is 5.5, the estimated coefficient suggests a 1.3% or $240 decline (evaluated at the mean annual rent per unit $19,243) in annual rent per unit.[20] In column (2), we control for county specific linear time trend as opposed to the year by county fixed effects. The estimated coefficient suggests that the result in column (1) is robust to an alternative specification. In Appendix Table A.3, we repeat the same exercise as Table 4.1 without including baseline controls. The results are strikingly stable, which reflects the nature of plausibly exogenous variations we are leveraging.

[20]When we aggregate the data to the annual level and repeat the same analysis, the point estimate is almost identical at –0.0024 (s.e. = 0.0028).

Table 4.1: Effect of High-Tide Flooding on Log Rental Rates

	(1)	(2)	(3)	(4)	(5)
N Days with HTF	-0.0023***	-0.0017***	-0.0010***	-0.0028***	-0.0023***
	(0.0004)	(0.0004)	(0.0003)	(0.0006)	(0.0006)
N Days with HTF x High Disruption			-0.0025***		
			(0.0006)		
N Days with HTF x Low Happening				0.0010	
				(0.0007)	
N Days with HTF x Low Worried					1.19e-5
					(0.0007)
Fixed-Effects:	———-	———-	———-	———-	———-
Zip Code	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes
Year-County	Yes	No	Yes	Yes	Yes
Distance to Coast	Yes	Yes	Yes	Yes	Yes
County	No	Yes	No	No	No
Varying Slopes:	———-	———-	———-	———-	———-
Year (County)	No	Yes	No	No	No
Observations	170,900	170,900	170,900	170,900	170,900

Note:
This table presents the effect of HTF on rents based on equation (3) for zip codes overlapping with the NOAA inundation map. 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 column (3), we present heterogeneous treatment effect by the mobility effect size to test if the disruption in mobility can explain the reduction in the rental rates. To that end, we first estimate the impact of HTF on overall number of trips for each state. Then using this state-specific HTF impact estimate, we classify states into large versus small mobility impact groups (above and below median impact size).[21] The point estimates in column (3) show that the impact of one additional day of HTF is more than twice larger for zip codes located in 10 states with high mobility impact. This suggest that impaired mobility is one of the important reasons behind the rental rate adjustments.

In columns (4)–(5), we estimate the impact for zip codes with different climate change beliefs. For

[21]Appendix Figure A.4 shows that at 10%, states naturally cluster into two groups (10 high effect states versus 11 low effect states).

this, we first create two dummy variables about county-level climate belief level using survey results from the Yale Climate Opinion Maps of 2013 (Howe et al. 2015). Specifically, we create variables "Low Worried" which takes value 1 if the fraction of respondents who said yes to a question asking whether they are worried about climate change is below 33% of the quantile.[22] Similarly, we create a variable "Low Happening" using responses to a question asking whether they believe climate change is happening. We then interact the climate belief variables with F_{zmt} from equation (3).

Interestingly, in both columns (4) and (5), we find no differential effect between high versus low believers, which is plausible as long as the reduction in the rental rates reflect lower physical amenity value from a housing service. That is, the utility cost of not being able to travel on the day of HTF would not necessarily higher or lower depending on whether they believe such inconvenience is caused by climate change or not. Importantly, a similar effect size for high versus low belief groups contrasts earlier findings in the literature that the housing price reflects flood risk only for high belief groups (Bernstein et al. 2019, Baldauf et al. 2020). The seemingly inconsistency can be explained once we account for the fact that a key determinant of the housing price is future expectations, which rarely is the case for rents. This emphasizes the importance of using rent as an outcome variable to measure the indirect costs of flood.

Figure 4.1 breaks down the effect in Table 4.1 column (1) by distance to the coastal line. For this, we separately estimate equation (3) for zip codes that belongs to each 10–miles distance bin {0–10, 10–20, $\cdots$, 40–50} to the closest coast. The estimated gradient suggests that the effect size gets smaller as zip codes gets farther away from the coastal line, which is plausible given that the impact of HTF is likely to be smaller for inland areas. However, it is also noteworthy that zip codes that are 30 to 40 miles away from the coast are still negatively affected (although with smaller magnitudes) by the HTF. This is likely to happen for at least two reasons. First, as discussed in Section 2.3, the affected area is wider for states with limestone bedrock. Second, disruptions caused by high-tide flooding may not be limited to the immediate affected area. For example, the paralysis of key nodes in the city-wide road network could create a ripple effect and lead to further disruptions throughout

[22] For instance, a zip code is classified as "Low Worried" if it belongs to a county with less than 54.4% of people responded that they are worried about climate change. Note, 54.5% is still substantially higher than the national average, which is 48%. This suggests that coastal community residents in general have much higher awareness on climate change than their inland peers.

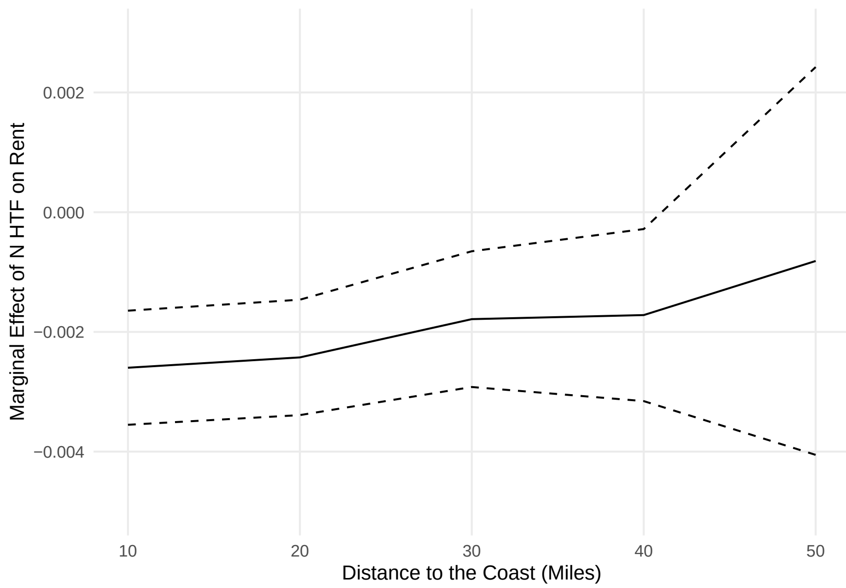


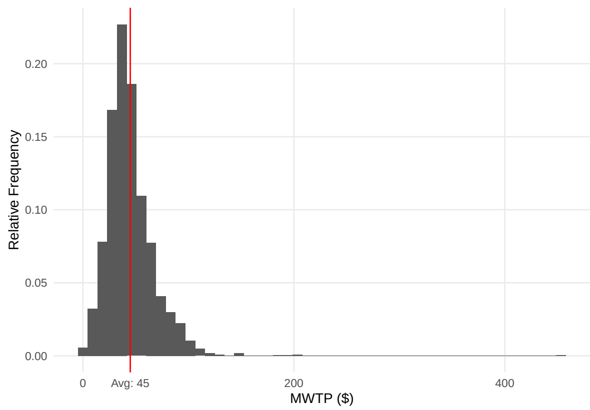
Figure 4.1: Distance–Price Gradient. This plot shows how the price effect of the HTF varies by the distance to the coastal line. We regress the number of days with HTF in the past 12 months on the log of monthly rent for each 10-miles distance bin with baseline controls. See text for more details

the city (Hauer et al. 2021).

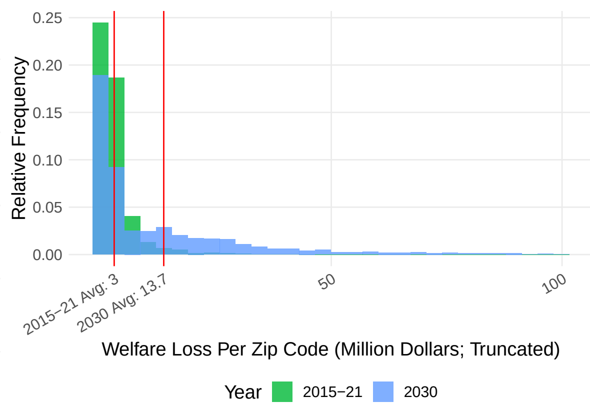
5 Discussion

Building on the hedonic framework (Rosen 1974), we conduct a back-of-the-envelop welfare calculations using the HTF impact on rents. As discussed earlier, we interpret the 0.23% or $45 reduction in rent resulting from one additional day of HTF (Table 4.1 Column (1)) as willingness-to-pay (WTP) to avoid disutility from floods, which is distinguished from direct damage on assets. Such an interpretation builds on the fact that HTFs rarely incur direct damage, but disrupt daily lives. Armed with this parameter, we calculate two welfare estimates: indirect costs from the Presidential Disaster Declaration (PDD) floods, which can be considered as "large" floods and welfare loss due to the HTF.

Welfare cost of PDD floods. As discussed, the impact of the HTF on rental rates can shed light on the inconvenience caused by broader classes of flood events (i.e., hurricanes, rainfalls, snow melts, etc). Given that larger floods tend to create much larger disruptions in people's lives—for instance, tens of thousands of flood victims are displaced for a prolonged period, the indirect cost estimated using the MWTP to avoid HTF should be regarded as a lower bound.



(a) MWTP



(b) Welfare Loss Per Zip Code

Figure 5.1: Welfare Loss from Floods. Panels (a) and (b) show the distribution of marginal willingness to pay to avoid HTF and welfare losses per zip code, respectively.

With this caveat, we take the average MWTP ($45) and multiply it by the number of households living in a county exposed to the Presidential Disaster Declaration (PDD) floods and by each events' duration.[23] The number of household for each county comes from the American Community Survey. For the duration of an event, we leverage the "incident window" in the PDD dataset from FEMA after making a few adjustments.[24]

Specifically, because incident window does not always correspond to the actual physical flood duration—its primary purpose is to establish the date range for damage or losses to be eligible for federal disaster assistance, and thus the window can be much wider than the actual flood duration—we first cap the incident window at a week to prevent overstating the duration (FEMA 2022). Further, we compare the incident window to an empirical flood duration, which we estimate using the cellphone data similar to our exercise in Section 3. For this, we separately estimate equation (2) for flood events with "incident window" 1-2, 3-4, 5-6, and 7+ days, and identify the number of days with statistically significant negative mobility impacts. Appendix Figure A.5 shows that (1) a PDD has a much larger and longer impact on the number of visits than a HTF and (2) incident window does not seem to overestimate the flood duration once we cap the window at a week. For instance, the number of visits is 20% lower than usual even after three days of PDD occurrence for PDD floods

[23]An implicit assumption behind this approach, which is widely used in the literature, is that the MWTP curve has a flat slope (Muehlenbachs et al. 2015, Bishop et al. 2020). If we assume instead that the MWTP curve is vertical, then it essentially means that we consider the duration of each flood event as one. If we assume a downward sloping MWTP curve instead, the indirect cost estimate will lie between the vertical and flat MWTP curve cases.

[24]Downloaded from https://www.fema.gov/openfema-data-page/disaster-declarations-summaries-v2 (Apr 29, 2023).

with incident window of 1-2 days (Appendix Figure A.5 (a)).

By combining information on the duration and the number of households, we find that in a given year over the 2018–2021 period, 26–69 million households were living in a county that has experienced a PDD flood,[25] and the corresponding household–days are 111 to 300 million. By multiplying the estimated indirect cost per flood day ($45 per household) with 200 million, which is the average household–days with PDD flood exposure over the 2018–2021 period, we find that the welfare cost is at least $9 billion per year, which is 28% of estimated direct cost of floods in the US ($32.1 billion) (Wing et al. 2022).[26] We believe this number is likely to be a lower bound because (1) inconvenience from large floods such as Presidential Disaster Declaration floods would be much larger than inconvenience from the HTF and (2) households exposed to smaller than PDD floods are excluded from this calculation.

Welfare cost of HTF. Impact of HTF on rents can also inform the welfare cost of HTF. For this, we use the annual welfare cost of HTF per year ($\$45 \times 5.5 = \$240$) from Section 4.[27] Using the number of households residing in the 2,102 zip codes that overlap with the inundation map, which totals 24 million households, we find the total welfare loss due to the HTF is $6 billion per year over 2015–2021 period.

While this is a strikingly large number given that HTF rarely incurs direct damage, it should be noted that this number is likely to be a lower bound for multiple reasons. For one, we did not account for 1,513 zip codes that are overlapped with the inundation map, but are not included in the Zillow rental data primarily because of less frequent transactions.[28] Further, if the hedonic price schedule itself shifts due to the HTF, the estimated welfare cost is a lower bound of true welfare cost

[25] A useful benchmark to assess this estimate comes from Wing et al. (2022), which have estimated the average annual exposure (AAE) of the current US population to flooding at 3.63 million. While this number is an order of magnitude smaller than the estimate we use, we want to note that the AAE estimate focuses on the population who are expected to have direct damage. In other words, the number of households exposed to *indirect* costs can be much larger.

[26] The $32.1 billion estimate captures damage from non-PDD floods as well, which implies that the direct damage from PDD floods only is likely to be smaller than $32.1 billion.

[27] Note, $240 is an average WTP for the entire sample, which is a product of average MWTP and average number of days with HTF. Alternatively, we could calculate zip code specific WTP (Figure 5.1 (b)) by multiplying zip code specific MWTP (Figure 5.1 (a), which is calculated by multiplying 0.23% with zip code specific average annual rent) with zip code specific HTF exposure. We find that the resulting average annual welfare loss per household is $230 per year, which is very close to $240.

[28] Assuming that these zip codes on average have similar rental rates as the 2,102 zip codes (i.e., $3 million welfare loss per zip code), taking these zip codes into account will increase the welfare cost to $10.8 billion.

(Banzhaf 2021).

Next, we take these numbers and project welfare losses in 2030 based on the expected number of HTF events. For this, we leverage findings from Thompson et al. (2021), which has projected the number of HTF per year for each NOAA site. The blue histogram in Figure 5.1 (b) shows the distribution of welfare loss for each zip code in 2030, which has been substantially shifted out in comparison to the histogram of 2015–2021 period because of more frequent HTF due to accelerating sea level rise. Consequently, an average welfare loss is more than four times larger than the 2015–2021 average. In total, the expected welfare loss from 2,102 zip codes is $29 billion.

While this numbers suggests that we need to take the impact of HTF seriously, it also needs to be interpreted with caution. For one, a flat MWTP curve approximation works well with small changes in amenity levels, but the number of days with HTF in 2030 is clearly a dramatic change. Relatedly, the impact is likely to be highly non-linear as a prolonged inundation is likely to impose an increasingly grave inconveniences on daily lives. Conversely, the welfare loss could be much smaller in the future, especially when cheap mitigation technologies become available.

6 Conclusion

With rising sea level, coastal communities are experiencing increasingly frequent HTFs, which is highly disruptive yet rarely destructive flood events from high tide, but limited empirical evidence exists on the impact of HTFs. By exploiting the spatial and temporal variations in the HTF prevalence, we estimate the impact of HTF on mobility and housing rents.

Using granular location data from mobile devices, we find direct evidence of disruption caused by HTF: on the day of HTF, the number of overall trips decline by 9.0%. Further, using zip code level rent data, we show that being exposed to one additional day of HTF in the past 12 months reduces rents by 0.23% or $240 per year. Importantly, the reduction in the rental rate from HTF is twice as large for zip codes in high mobility impact states, which shows that impaired mobility is capitalized into the rental rates. We also find that the impact is similar for high versus low climate belief zip codes, which suggests that physical inconvenience reduces utility from housing services irrespective of one's belief.

Building on the hedonic model, we show that a lower bound of inconvenience cost from large flood events (i.e., Presidential Declaration Disaster floods) over the 2018–2021 period is \$9 billion per year, which is 28% of the estimated direct cost of floods (Wing et al. 2022). Further, the welfare cost of HTF is estimated to be additional \$6 billion dollars per year over the 2015–2021 period, and is expected to become as large as \$29 billion per year in 2030.

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A Additional Tables and Figures

Table A.1: Percentage of Raw Visit Counts by NAICS Codes

Sector Title	NAICS Code	Pct. of Visit Counts	Pct. of POIs
Accommodation and Food Services	72	25.68	23.54
Retail Trade	44	16.19	17.35
Arts, Entertainment, and Recreation	71	14.46	7.63
Real Estate Rental and Leasing	53	11.61	2.46
Retail Trade	45	9.72	5.99
Health Care and Social Assistance	62	6.84	14.68
Educational Services	61	5.82	3.38
Other Services (except Public Administration)	81	4.48	15.21
Transportation	48	1.49	0.63
Finance and Insurance	52	0.62	2.91
Public Administration	92	0.47	0.69
Information	51	0.38	0.75
Professional, Scientific, and Technical Services	54	0.37	1.22
Construction	23	0.35	0.82
Manufacturing	31	0.27	0.65
Wholesale Trade	42	0.25	0.55
Manufacturing	32	0.23	0.50
Manufacturing	33	0.21	0.29
Warehousing	49	0.21	0.30
Administrative and Support and Waste Services	56	0.16	0.27
Management of Companies and Enterprises	55	0.15	0.13
Utilities	22	0.04	0.06
Agriculture, Forestry, Fishing and Hunting	11	0.00	0.01
Mining	21	0.00	0.00

Note:
This table presents the percentage of raw visits and POI counts by NAICS industry codes in our sample.

Back to Section 2.2.

Table A.2: Effect of High-Tide Flooding on Log Normalized Visits

	(1)	(2)	(3)	(4)	(5)
HTF Event	-0.094***	-0.094***	-0.092***	-0.091***	-0.091***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
Cutoffs	All	20 Visits	30 Visits	40 Visits	50 Visits
Observations	3,054,951	3,006,738	2,628,339	2,077,542	1,409,865

Note:
This table presents the effect of HTF on normalized visits based on equation (1) for zip codes overlapping with the NOAA inundation map. Each column represents a separate regression with different cutoffs on average weekly visits. All outcome variables are in log scale and baseline controls are included in all columns. Standard errors are clustered at the county level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

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Table A.3: Effect of High-Tide Flooding on Log Rental Rates (Without Baseline Controls)

	(1)	(2)	(3)	(4)	(5)
N Days with HTF	-0.0023***	-0.0017***	-0.0010***	-0.0028***	-0.0024***
	(0.0004)	(0.0004)	(0.0003)	(0.0006)	(0.0006)
N Days with HTF x High Disruption			-0.0025***		
			(0.0006)		
N Days with HTF x Low Happening				0.0010	
				(0.0007)	
N Days with HTF x Low Worried					3.07e-5
					(0.0007)
Fixed-Effects:	———-	———-	———-	———-	———-
Zip Code	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes
Year-County	Yes	No	Yes	Yes	Yes
Distance to Coast	Yes	Yes	Yes	Yes	Yes
County	No	Yes	No	No	No
Varying Slopes:	———-	———-	———-	———-	———-
Year (County)	No	Yes	No	No	No
Observations	170,996	170,996	170,996	170,996	170,996

Note:
This table presents the effect of HTF on rents based on equation (3) for zip codes overlapping with the NOAA inundation map. All outcome variables are in log scale and baseline controls excluded in all columns. Standard errors are clustered at the county level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

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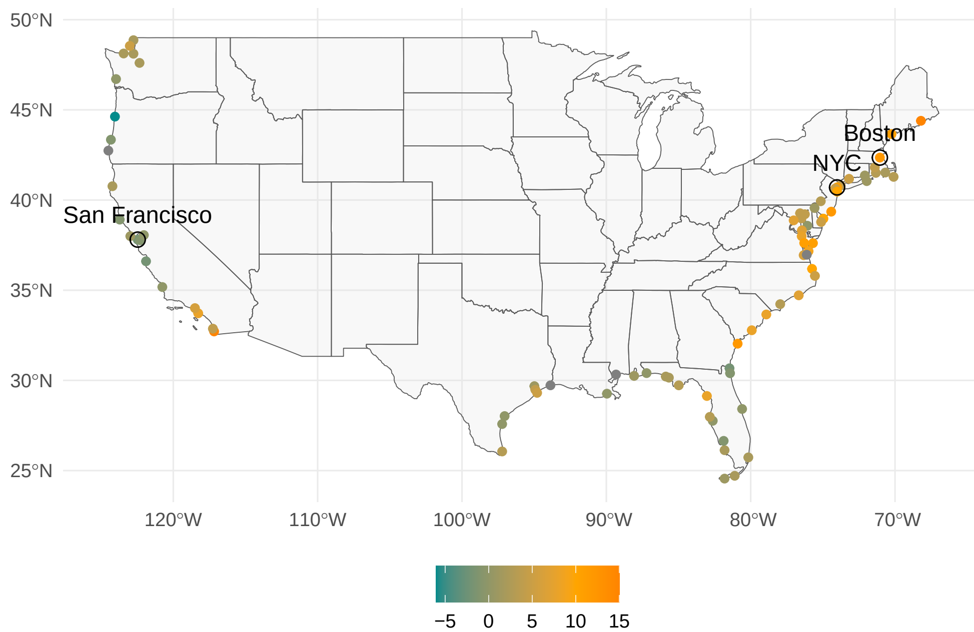

Figure A.1: Location of NOAA Gauge Stations and Change in the Annual Number of Days with HTF between 2001 and 2022. This figure depicts 84 NOAA gauge stations within the contiguous US that has flood thresholds from Sweet et al. (2018). The color illustrates the change in the number of days with HTF between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

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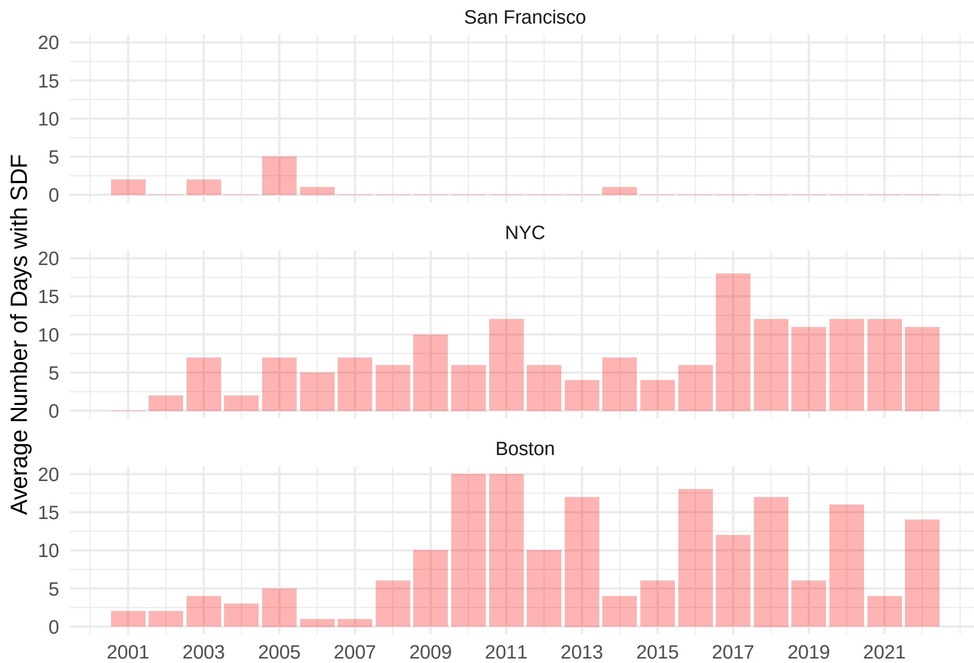

Figure A.2: Number of days with HTF for Three Different Cities. These figures show the number of days with HTF for Boston, NYC, and San Francisco over 2001-2022.

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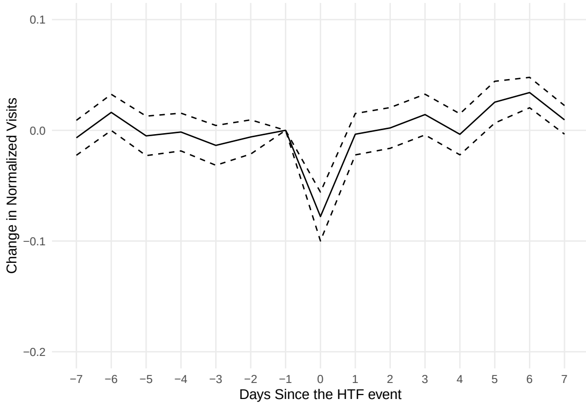
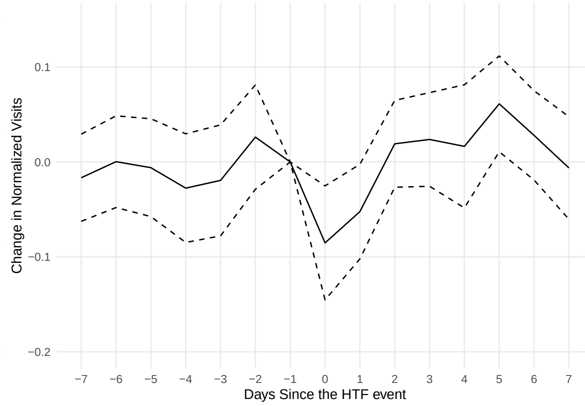
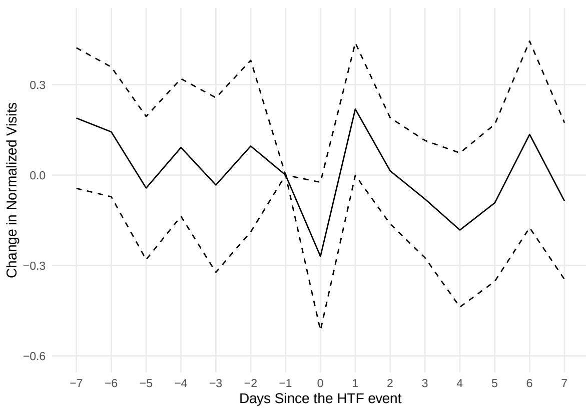


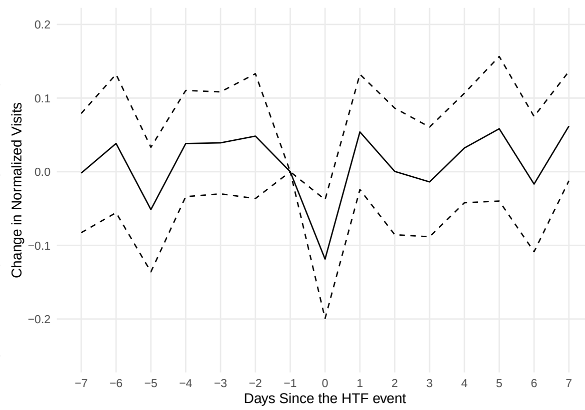
(a) Automotive Repair



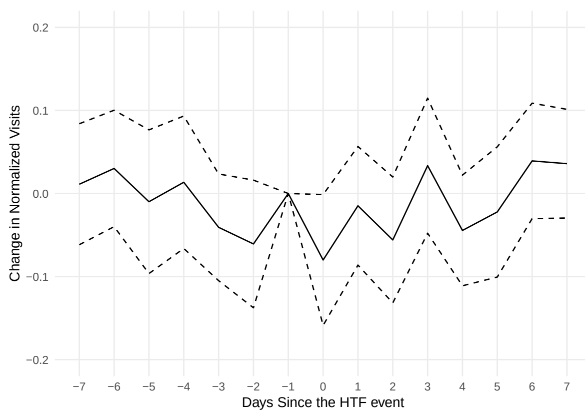
(b) Electronic Repair



(c) Home and Garden Repair



(d) Furniture Repair



(e) Appliance Repair

Figure A.3: The effects of HTF on the number of daily visits to selected zip codes across subcategories in other services. These plots show the HTF impact on the number of visits during 7 days before and after the HTF event. We control for the effects of larger and moderate flood events, precipitation, the fraction of population with college degree, the fraction of minority populations, median income, the fraction of rental units, county by year fixed effects, and zip code by day-of-week-of-month fixed effects. See text for more details.

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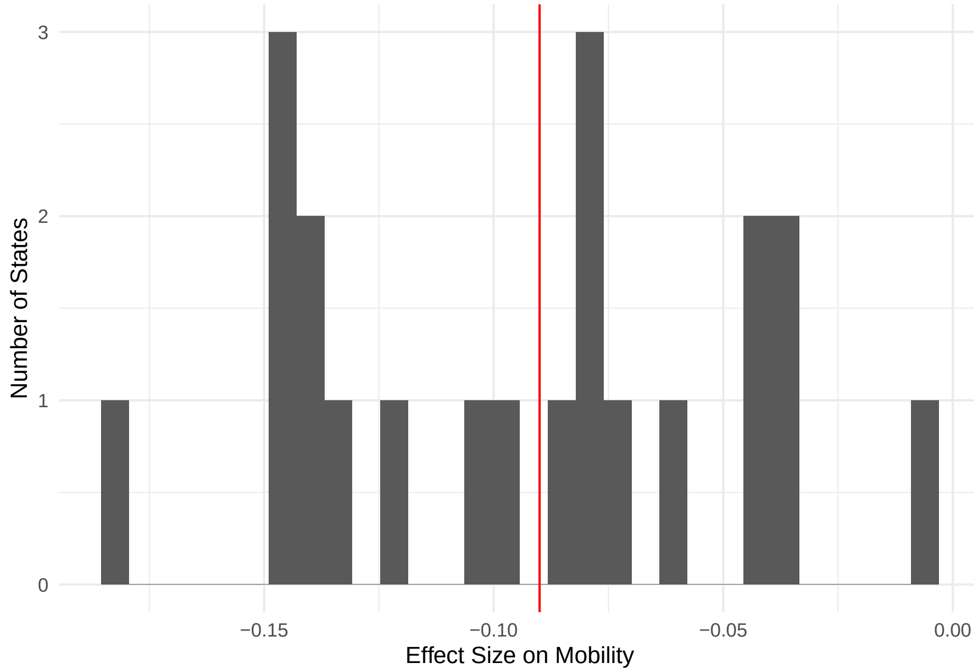

Figure A.4: The Distribution of the Impact of HTF on Mobility. The histogram shows the distribution of the state-specific impact of HTF on overall number of trips.

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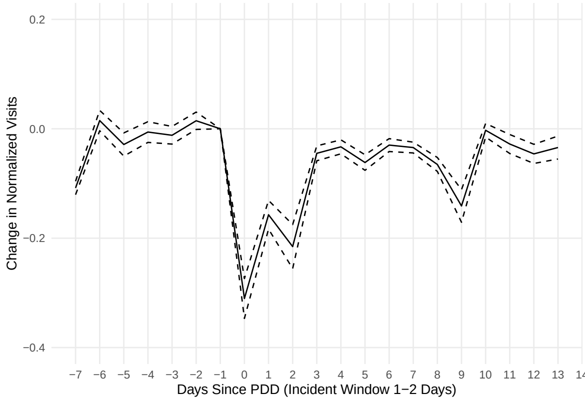
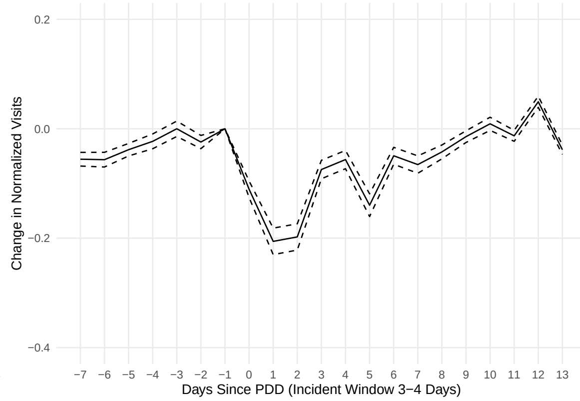
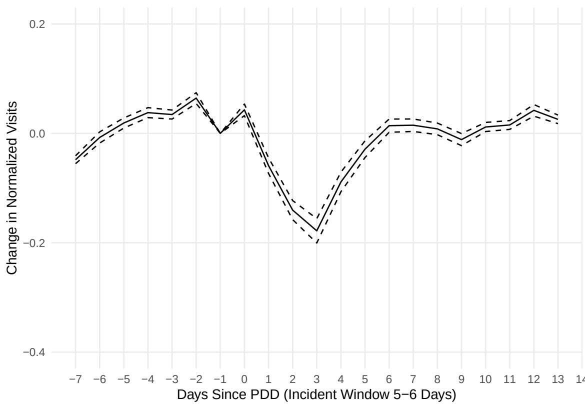


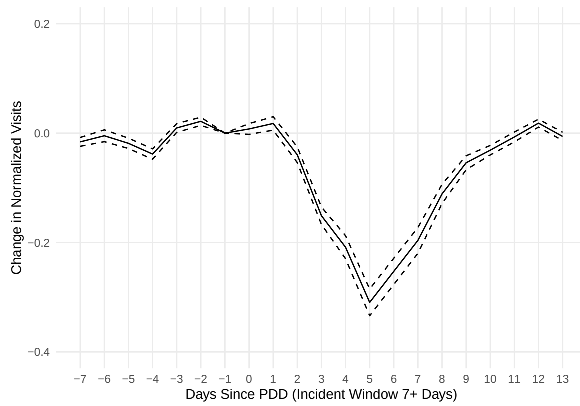
(a) 1- and 2-day PDD Flood



(b) 3- and 4-day PDD Flood



(c) 5- and 6-day PDD Flood



(d) 7+ day PDD Flood

Figure A.5: The effects of PDD flood on the number of daily visits to selected zip codes across subcategories in other services. These plots show the HTF impact on the number of visits during 7 days before and 14 days after the HTF event. We control for the effects of larger and moderate flood events, precipitation, the fraction of population with college degree, the fraction of minority populations, median income, the fraction of rental units, county by year fixed effects, and zip code by day-of-week-of-month fixed effects. See text for more details.

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