Beyond Asset Losses: Estimating the Economic Cost of Floods

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Abstract

While a theoretically consistent measure of flood costs is welfare loss, existing estimates are primarily based on asset losses. This paper leverages high tide flooding (HTF)—highly disruptive yet rarely destructive small-scale coastal floods—to estimate the economic cost of floods. We find that on HTF days, visits to places decrease by 5%. Further, each additional day of HTF in the past year reduces rents by 0.24%, which we interpret, based on the hedonic model, as the marginal willingness-to-pay to avoid disruptions from HTF. Using this parameter, we estimate a lower-bound annual economic cost of Presidential Disaster Declaration floods at $4 billion.

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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 flood waters 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)

Economic theory posits that the true cost of floods is the utility loss they create, which includes not only asset losses, such as damaged properties, but also a wide range of additional costs arising from disruptions to economic activities and daily life (these additional costs are referred to in this paper as "economic costs"). However, widely referenced cost estimates such as National Oceanic and Atmospheric Administration (NOAA)'s "Billion-Dollar Weather and Climate Disasters" are primarily based on asset losses due to measurement challenges (Smith and Katz 2013).[1] This practice, which may substantially underestimate the true cost, is not merely a theoretical concern: the federal government has emphasized developing estimates for currently non-monetized costs of natural disasters as a critical step toward more robust regulatory analyses in the face of climate change (National Science and Technology Council 2023).

To address this gap, we provide one of the first estimates of the economic cost of floods by leveraging high tide flooding (HTF), a highly disruptive yet rarely destructive small-scale coastal flood caused by oceanic dynamics.[2] Because HTF events can be viewed as random draws from an underlying distribution—much like fluctuations in extreme temperatures—they offer plausibly exogenous variation and strong identification properties (Dell et al. 2014). Our analysis begins by examining the impact of HTF on mobility, offering "first-stage" evidence of its disruptive effects. Next, we estimate HTF's effect on rental rates. Building on the hedonic model, we interpret this coefficient as the willingness-to-pay (WTP) to avoid HTF, or a lower-bound economic cost of floods. Focusing on HTF is essential for this interpretation, as it avoids the bundled treatment problem of larger floods,

[1] There are at least two additional approaches for disaster cost estimation. The first approach aims to identify the relationship between disaster and macroeconomic outcomes. (Nordhaus 2010, Strobl 2011, Cavallo et al. 2013, Hsiang and Jina 2014, Desmet et al. 2021). The second approach focuses on estimating a specific dimension of economic costs (e.g., labor market outcomes) (Gallagher and Hartley 2017, Deryugina et al. 2018). This paper departs from these studies by estimating a micro-founded yet comprehensive economic cost of floods.

[2] HTF is often referred to as "nuisance" or "sunny day" flooding as well.

which incur both asset losses and economic costs.[3] Finally, using this parameter, we estimate a lower-bound economic cost of Presidential Disaster Declarations (PDD) floods.

For empirical exercises, we construct historical HTF occurrence data by comparing daily water level records with flood thresholds for each of the 84 NOAA gauge stations across coastal states in the contiguous US. We link this with zip code level monthly rental rates (2015–21) and daily visits data (2018–21) from Zillow and Safegraph. To determine the area inundated by the HTF (i.e., the spatial extent of the HTF), we use the HTF inundation map from NOAA.

Our analyses produce three main findings. First, using the distributed lag model, we find that on the day of HTF, the average number of visits drops by 5% in inundated zip codes. In contrast, the number of visits immediately before HTF is strikingly similar to the rest of the days, consistent with the assumption that HTF occurrences are plausibly random. Moreover, we show that these disruptive effects often spill over into adjacent—but not directly inundated—areas, particularly in cities with less resilient road networks. By investigating the impact by destination categories, we show that HTF disrupts access to a wide range of places including essential infrastructures, urban amenities, and workplaces. This suggests that the cost of impaired mobility from floods extends far beyond a nuisance, leading to losses in health, learning, leisure, productivity, and income.

Turning to rental rates, we first posit that individuals form beliefs about HTF likelihood during the rental period based on recent exposure, consistent with prior evidence that individuals use past experience with similar hazards to update beliefs about future risks (Davis 2004, Bin and Landry 2013, Deryugina 2013, Gallagher 2014, Hong et al. 2019, Choi et al. 2020). Then, by exploiting year-to-year variations in HTF frequency, we find that having one additional day of HTF in the past 12 months reduces rental prices by 0.24% or $48. Notably, HTF exposures have no effect on flood insurance claims, suggesting that the reduction in rental rates arises from HTF's negative impact on the property's expected use value rather than physical damage.

Building on the hedonic model, we interpret $48 as MWTP to avoid disruptions caused by HTF, or a lower bound daily economic cost from floods. Importantly, we do not use housing prices as an outcome variable because, unlike rental rates, which reflect individuals' beliefs about a property's

[3]In addition to making it difficult to separate economic costs from asset losses, large floods can also complicate price signals, a key input to hedonic regressions. For instance, a housing supply shortage or improvements in housing quality from post-flood rebuilding efforts may drive up rental rates, obscuring the true economic cost of floods.

use value, housing prices capture both beliefs about use value and resale prices.[4] Further, consistent with the spillover effects documented in the mobility analysis, rental rates in uninundated coastal zip codes decline only for those in cities with less resilient road networks, suggesting that impaired mobility is a key mechanism driving rent adjustments. Our findings are robust to alternative measures for beliefs such as HTF exposures from longer historical periods (e.g., 24 months) or scientific forecasts on the future number of HTF days.

Using the estimated parameter, we calculate the economic cost of large floods, using the Presidential Disaster Declaration (PDD) floods as examples. We take $48 and multiply it by the number of households living in zip codes exposed to PDD floods and by the duration of each event. The resulting economic cost is as large as $4 billion per year over the 2018–21 period, which is comparable to the $5 billion in flood insurance claims and federal disaster relief provided for the same set of PDD floods.[5] Although $4 billion is already substantial, we believe this number is likely to be a lower bound because (1) disruptions from large floods are much more substantial than those from HTF and (2) larger floods oftentimes destroy assets, which are important utility shifters. Our findings suggest that ignoring the economic costs can substantially underestimate the true cost of floods.

Related literature. This paper contributes to four distinct strands of literature. First, it complements earlier studies estimating the cost of natural disasters. These studies typically focus on (1) damage to physical assets (Smith and Katz 2013, Wing et al. 2022), (2) specific dimensions of economic costs such as labor market impacts (Deryugina et al. 2018) and financial distress (Gallagher and Hartley 2017), or (3) rely on macroeconomic outcomes (Nordhaus 2010, Strobl 2011, Cavallo et al. 2013, Hsiang and Jina 2014, Desmet et al. 2021) for cost estimation. This paper provides a new estimate of the currently non-monetized economic costs of floods by integrating an innovative identification strategy with the hedonic framework. The findings suggest that ignoring these economic costs can lead to a significant underestimation of the true cost of floods, potentially compromising the accuracy of cost-benefit analyses of flood policies (National Science and Technology Council 2023). Moreover, our estimates provide valuable insights into the economic costs of other natural disasters, such as wildfires and earthquakes, which also trigger defensive behaviors and income losses (National

[4] In Lee and Zheng (2025a), we find that the impact of HTF on rental and housing prices are significantly different.

[5] These estimates suggests that the economic cost can be nearly half of the total costs, which is consistent with previous studies (Hallegatte 2008, Koks et al. 2015, Benetton et al. 2022).

Research Council 1999, Jones et al. 2016, Borgschulte et al. 2022).

Second, this paper contributes to the voluminous hedonic literature on flood risk (Hallstrom and Smith 2005, Bin and Landry 2013, Bosker et al. 2019, Gibson and Mullins 2020, Hino and Burke 2021). Previous studies often estimate individuals' WTP to avoid catastrophic flood risks, comparing these estimates to benchmarks such as flood insurance premiums or objective risk probabilities to assess market efficiency or consumer rationality. A key assumption underlying these analyses is that asset losses are the sole driver of housing price adjustments. We depart from these papers by (1) focusing on an alternative type of flood risk, which allows us to target a different parameter, and (2) highlighting economic costs as a novel mechanism behind housing market adjustments.

Third, despite scientific findings that HTF will evolve very soon from an occasional nuisance to a chronic problem (50+ days with HTF per year) for many coastal cities (Thompson et al. 2021), a large literature on flood predominantly focus on catastrophic decadal- or centennial-scale events (e.g., Ouazad and Kahn (2022); Deryugina (2017); Gallagher (2014)). This paper expands a small and nascent literature on HTFs (Hino et al. 2019, Hauer et al. 2021, Benetton et al. 2022, Hauer et al. 2023, Mueller et al. 2024, Lee and Zheng 2025a) by providing the first national-scale empirical evidence on their mobility and housing market impacts.

Lastly, we build on recent studies that have utilized highly frequent and geographically detailed mobile phone data to measure spatial patterns such as consumption and recreational demand (Miyauchi et al. 2021, Knittel et al. 2023), economic activities (Atkin et al. 2022, Gupta et al. 2022b, Li et al. 2023, Kreindler and Miyauchi 2023), and social interactions (Athey et al. 2021, Couture et al. 2022). Our analysis reveals that mobile phone data is valuable in natural disaster settings as well, allowing researchers to precisely identify affected areas and infer the source of utility losses from floods with unprecedented granularity in both space and time.

This paper proceeds as follows. Section 2 lays out a framework that conceptualizes the economic cost and guides empirical analysis. Section 3 provides background on the HTF, details the data sources, and provides summary statistics. Section 4 analyzes the impact of HTF occurrence on mobility, and Section 5 studies the impact of HTF on rental rates. Section 6 estimates the economic cost of PDD floods. Section 7 concludes.

2 Conceptual Framework

We introduce a simple hedonic model that examines the trade-off between housing prices and risks to define economic costs, and to guide our empirical analysis (Gayer et al. 2000, Davis 2004, Viscusi and Gayer 2005, Bosker et al. 2019). Individuals maximize expected utility over two states of the world "dry (D)" and "flood (F)". Utility in each state $j \in \{\text{D, F}\}$ are $U = U_j(z, x)$ where z is a vector of housing characteristics and x is a numeraire. Because floods incur serious disruptions in daily life (e.g., impaired mobility), $U_D > U_F$ for all values of (z, x).[6] Individuals rent a house for a rental period at a total cost of r, which is a function of z and p, the subjective probability of flood during a rental period. Then, each individual's bid function consists of (r, p) pairs that satisfy equation (1) where y is income. In a competitive market, rents reflect an individual's WTP for a house.

$$V = pU_F(z, x) + (1 - p)U_D(z, x) \quad s.t. \quad y = x + r(z, p) \tag{1}$$

The first order condition in equation (2) implies that the gradient of the hedonic price schedule with respect to subjective flood risk ($\frac{\partial r}{\partial p}$) is equal to the monetized utility reduction due to a marginal increase in the frequency of HTF ($\frac{U_F(x,z)-U_D(x,z)}{p\partial U_F/\partial x+(1-p)\partial U_D/\partial x}$), which we refer to as the "economic cost" of floods.[7] Put differently, our definition reflects the additional amount of money individuals would require to restore the initial level of utility following a marginal increase in p. Importantly, equation (2) implies that the economic cost can be empirically estimated as long as we can measure p.

$$\frac{\partial r}{\partial p} = \frac{U_F(x, z) - U_D(x, z)}{p\partial U_F/\partial x + (1 - p)\partial U_D/\partial x} \tag{2}$$

Take theory to data. Equation (2) provides guidance for our empirical exercise. First, given that HTF primarily impairs road conditions, which critically determines access to various destinations people value, the impact of HTF on the number of trips can be a direct test if $U_D > U_F$ is true.

Second, equation (2) suggests that our empirical exercise requires data on the belief on the prob-

[6] For instance, utility from tasty food (an example of x) diminishes if gatherings are canceled, and the value of proximity to work (an example of z) diminishes when access to the workplace is restricted, all due to flooded roads.

[7] Because y is exogenous, equation (1) abstracts away from an income or leisure shock channels. For instance, limited access to the workplace or lower foot traffic may reduce income for business owners. Similarly, increased commuting time could reduce leisure. By endogenizing time choice, the model can more directly incorporate these channels.

ability of floods during the rent period (i.e., belief about the future). To proceed, we assume that individuals form their subjective probability of HTF based on recent exposure, consistent with prior evidence that individuals use past experience with similar hazards to update beliefs about future risks (Davis 2004, Bin and Landry 2013, Deryugina 2013, Gallagher 2014, Hong et al. 2019, Choi et al. 2020).[8] While we remain agnostic about the theoretical underpinnings of this belief formation process, earlier studies suggest it is consistent with both behavioral biases (e.g., myopia) or a Bayesian learning model.

An important underlying assumption behind measuring p using recent HTF exposure is that recent exposure influences r solely through p. This might not hold if HTF has lasting effects, such as damage on properties or the degradation of local amenities. We alleviate these concerns using the visits and flood insurance claims data in Section 5. Further, this assumption also suggests that using housing prices as opposed to rental rates in hedonic regression can be problematic because HTF is likely to affect housing prices not only through p but also through changing individuals' expectations on future housing prices. Indeed, Bishop et al. (2020) points out that rental rates may better reflect current amenity flows than housing prices.

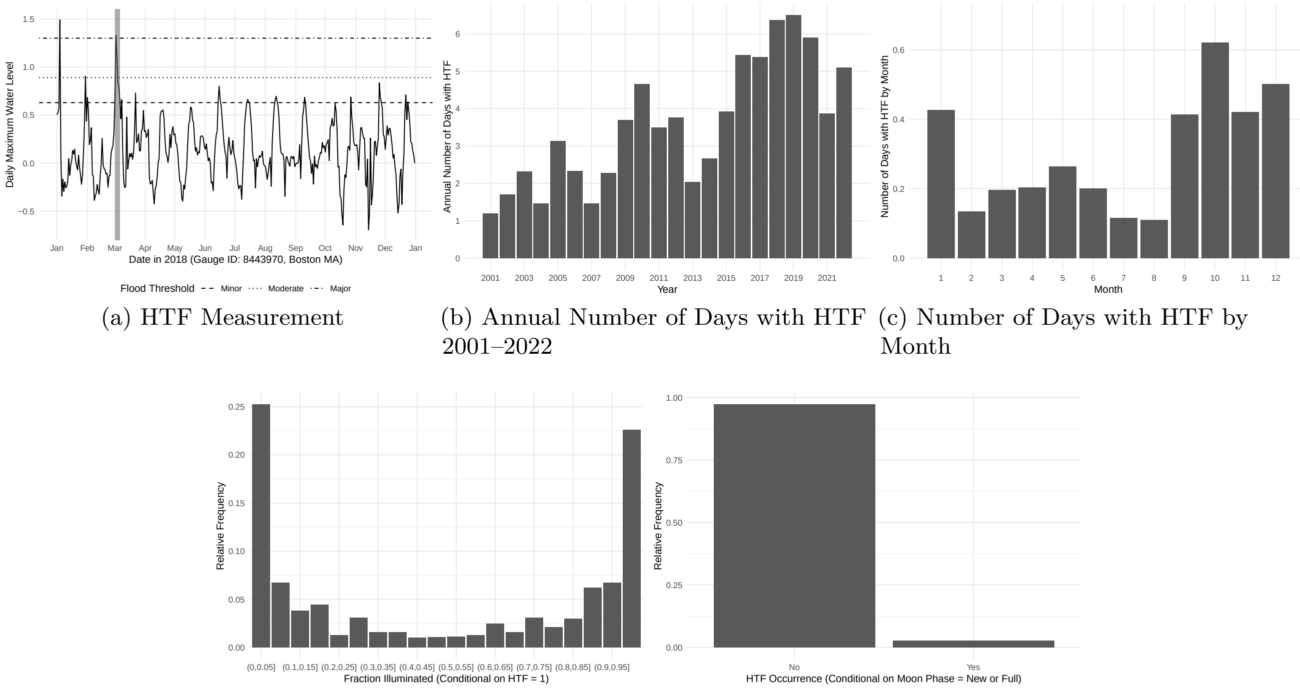
Finally, equation (1) highlights that the HTF based economic cost estimates underestimates the economic cost of larger floods for two reasons. To highlight this, it is helpful to divide the vector of z into two segments: z_1, structural attributes of a property, such as the building's physical condition, and z_2 that captures amenities like proximity to work. Now, as detailed in Section 5, HTF inflicts minimal direct damage and thus rarely alters z_1. In contrast, larger flood events will negatively impact z_1 (e.g., roof damage), which will reduce utility derived from given (z_2, x). Note, even in the absence of change in z_1, the gap between U_D and U_F will be greater for larger floods because the level of disruptions will be higher—for instance, more extensive road closures are likely to happen.

3 Background and Data

3.1 High Tide Flooding

HTF: measurement, trends, and impacts. The National Weather Service classifies flood events into three categories based on their impacts: minor floods, which result in minimal or no property dam-

[8] In Section 5, we also show that our results are robust to alternative measurements.



(a) HTF Measurement

(b) Annual Number of Days with HTF 2001–2022

(c) Number of Days with HTF by Month

(d) Moon Illumination on HTF Days

(e) Prob. of HTF Given New or Full Moon

Figure 3.1: HTF Measurement and its Characteristics. Panel (a) illustrates HTF measurement using Gauge ID 8443970 in 2018. Panel (b) shows the annual number of HTFs during 2001–22 averaged over 84 NOAA gauge stations in the contiguous US. Panel (c) shows the average monthly number of days with HTF during 2001–22. Panels (d) and (e) show the distribution of moon illumination conditional on the HTF occurrence and the probability of HTF conditional on new or full moon phase.

age but may pose public threats such as road inundation; moderate floods, which involve inundation of structures and roads near the stream and may require evacuations or the relocation of property; and major floods, characterized by extensive inundation of structures and roads, significant evacuations, and widespread disruption (National Weather Service 2019). Building on these definitions, NOAA defines HTF as an event in which the daily maximum water level falls between the minor and moderate flood thresholds (Sweet 2018).

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

To measure HTF spatially—that is, to identify areas subject to high tide flooding—we use NOAA's HTF inundation map.[9] This map delineates areas projected to be inundated when water levels reach the site-specific "minor" threshold. The mapping uses a "bathtub" approach: any location where land elevation is lower than the modeled water surface is classified as inundated. The water surface is constructed by interpolating across tide gauge stations at the minor flood threshold. The HTF inundation map is produced in essentially the same way as NOAA's Sea Level Rise inundation map products, which have been widely used in previous studies (Bernstein et al. 2019, Baldauf et al. 2020, Giglio et al. 2021).[10]

Appendix Figure A.1 illustrates the map for the Mid-Atlantic region. Notably, inundated areas are not limited to locations directly adjacent to the ocean; in some cases, they extend far inland via connected water systems—most notably tidal rivers, such as the Delaware and Hudson Rivers—where tidal influences can propagate well upstream.[11]

While tidal movement is not a new phenomenon, HTF has become increasingly prevalent in recent years due to sea level rise. Over the past two decades, the average number of days with HTF in the contiguous U.S. has more than tripled (Figure 3.1 (b)), and this trend is expected to accelerate—by mid-2040, many cities along the Atlantic Coast are projected to experience 50-100 days of HTF annually (Thompson et al. 2021).

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

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

[10] In both cases, inundation is determined by the condition Inundated = (Land Elevation $\leq$ Water Surface). For the HTF map, the water surface is defined as mean higher high water (MHHW) plus the site-specific minor flood threshold; for the Sea Level Rise (SLR) map, it is MHHW plus the selected SLR scenario (e.g., 2 ft). See NOAA (2017) for further details.

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

losses from HTF are minimal as we discuss in Section 5.

HTF as a research design. A critical assumption in our empirical strategy is that HTF occurrence—both in terms of year-to-year frequency (Section 5) and precise timing (Section 4)—is plausibly random. This assumption is supported by prior studies showing that HTF is driven by multiple interrelated physical factors, including large-scale atmospheric and oceanic patterns such as the El Niño–Southern Oscillation (ENSO), as well as localized conditions like wind speed, water density, and tidal forces—all of which vary substantially over time and space (Sweet 2018). Plausibly random variations in HTF occurrence are similar in spirit to numerous studies that leverage weather shocks—such as temperature, precipitation, and windstorms—which are often modeled as random spatial realizations and "offer strong identification properties" (Dell et al. 2014).

Consistent with this, Figure 3.1(b) shows that even after averaging out gauge-specific idiosyncrasies, HTF frequency varies substantially from year to year. Similarly, binned scatterplots in Appendix Figure A.2 demonstrate that, after conditioning on year and gauge fixed effects, HTF exhibits only weak serial correlation across years—making the annual number of HTF events resemble a plausibly random draw from an underlying distribution.

At the daily level, one might worry that HTF is correlated with other natural phenomena. For example, Figure 3.1(a) suggests a relationship between water levels and the moon phase, and (c) reveals seasonality in HTF occurrences. However, while it is true that HTFs tend to cluster around full or new moon phases (Panel (d)), these phases occur frequently throughout the year, so the probability of an HTF on any given moon phase day remains low at 3% (Panel (e))—suggesting that moon phase alone has limited predictive power for the precise timing of HTF events.[12]

3.2 Data Description

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

[12]The conclusion holds even when restricting the sample to seasons and locations where tidal forcing is a stronger predictor of HTF—fall and winter in Maine, Oregon, Washington, and San Diego, as identified by Sweet (2018). While the share of days with HTF conditional on relevant moon phases in this subsample doubles relative to the full sample, it remains low at 5%.

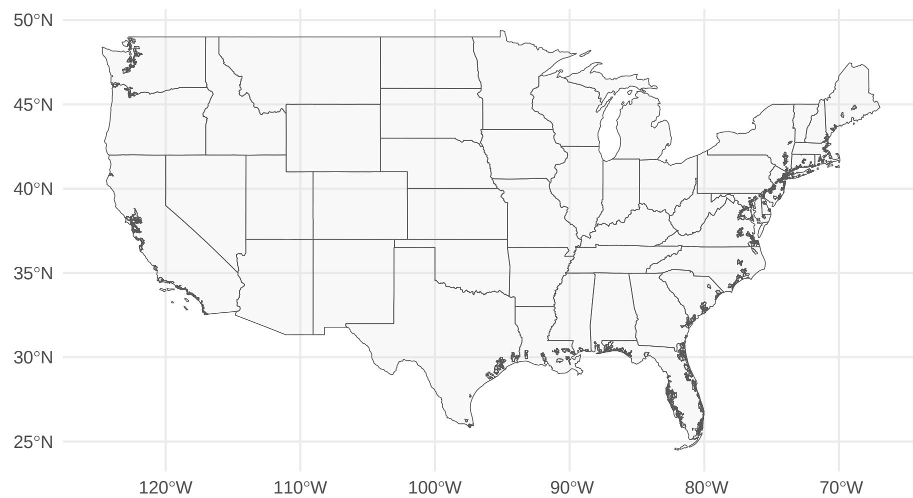


Figure 3.2: Map of the Study Area. This figure depicts our main sample, which consists of 1,471 zip codes that have non-missing rental rate records over 2015–21 and have an overlap with the NOAA inundation map.

(2018) (See Appendix Figure A.3 for gauge locations).[13] As detailed in Section 3.1, we compare the time series of daily water levels to gauge-specific flood thresholds and define a binary indicator that equals 1 when the daily water level falls between the minor and moderate flood thresholds. To connect zip codes with HTF events, we match each zip code to the nearest NOAA gauge station.

Mobility. We use mobile phone based visit counts records from SafeGraph Monthly Patterns data, which documents the daily number of visits to a universe of places in the US from roughly 10% of mobile devices in the US since 2018 (Parolin and Lee 2021).[14] SafeGraph data has been used to study recreational demand (Knittel et al. 2023), economic activity (Chen and Pope 2020, Atkin et al. 2022), and social interactions (Athey et al. 2021). It has also been shown to be demographically representative at the national level (Chen and Pope 2020, Athey et al. 2021). We observe each place's exact location and the North American Industry Classification System (NAICS) code. We aggregate place level visit records to create a balanced panel of visit counts at the day by zip code level for the period of 2018-21.

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

[14]The types of places included in the data are places of business (e.g., retailers and hospitals), leisure (e.g., parks), work (e.g., manufacturing plants), travel (e.g., transit stops), and community living spaces (e.g., apartments). Excluded from the data are single-family houses, geographic features such as rivers, forests, and lakes, as well as transit routes like roads. See https://docs.safegraph.com/docs/definition-of-a-place for more details (accessed on Aug 15, 2024). Also, see Appendix Table A.1 for the relative frequency of destination categories in the data.

Rental rates. We use Zillow Observed Rent Index (ZORI) for rental rates.[15] Zillow constructs the index by taking the weighted average of asking prices within the 35th to 65th percentile price range on properties repeatedly listed for rent on Zillow.[16] The index is dollar-denominated and we adjust it for inflation using CPI. We use the zip code-level data from March 2015 to December 2021. 1,471 zip codes within the 22 coastal states in the contiguous US that have both rental information and an overlap with the NOAA inundation map form the main analysis sample (see Figure 3.2).

ZORI has been widely used in prior research and shows a high correlation with other rental data sources, including the Fair Market Rent Index from the Department of Housing and Urban Development (HUD), median rent estimates from the American Community Survey (ACS), and the Rent of Primary Residence component of the CPI from the Bureau of Labor Statistics (BLS) (Gupta et al. 2022a). We choose to use ZORI because these alternative data sources lack the spatial and temporal granularity and coverage provided by ZORI.

Flood insurance claims. We use the National Flood Insurance Program (NFIP) claims data from FEMA to investigate the impact of HTF on asset losses. The data have over 2 million individual property level claims information including claims dollar amount from 1978–2021. We aggregate the data to the zip code by month level and merge it with the coastal flood history data.

Summary statistics. Table 3.1 shows summary statistics for key variables used in our empirical exercise from our primary sample in Figure 3.2. Panel A shows two key variables for the mobility impact analysis. The average number of visits per day at the zip code level is 3,405.[17] Also, the mean daily probability of HTF occurrence (0.016, which is rounded up to 0.02), implies an average of 5.6 HTF days per year.

In Panel B, we present descriptive statistics for the rent and NFIP impact analyses. Several points are worth noting. First, the median distance between a zip code *centroid* and a NOAA gauge station is 13.6 miles, indicating that HTF exposure is well-measured for most zip codes. In Sections 4 and 5,

[15]Bishop et al. (2020) points out that using spatially aggregated data like ZORI may complicate estimating MWTP using hedonic model because the derivative of the hedonic price function at the mean amenity level typically does not match the mean of the derivatives. Nevertheless, because we operate under the assumption that the MWTP curve is flat in line with existing literature, the two objects are identical (for more details, see Muehlenbachs et al. (2015)).

[16]To improve representativeness and better capture the broader rental market—not just units listed on Zillow—observations that are overrepresented in the Zillow data relative to Census data are down-weighted, while those that are underrepresented receive greater weight. For details, see https://www.zillow.com/research/methodology-zori-repeat-rent-27092/ (accessed on Mar 2, 2023).

[17]A small number of observations (0.4%) has zero visits in a given day.

Table 3.1: Summary Statistics for Key Variables

Variables	Min.	Max.	Median	Mean	Std.Dev.	N
Panel A: Mobility Impact Data						
N of Daily Visits	0	57,735	2,606	3,405	2,992	2,149,131
If HTF	0	1	0	0.02	0.13	2,149,131
Panel B: Rent and NFIP Impact Data						
Distance bewteen Zip Code and Gauge	0.3	122	13.6	20.9	21.8	119,507
Monthly Rental Rates	12.5	32,656	1,531	1,702	1,024	119,507
N HTFs (in Past 12 Months)	0	44	5	5.6	4.9	119,507
N Larger Floods (in Past 12 Months)	0	11	0	0.48	0.99	119,507
N NFIP Claims per Month	0	3,986	0	0.79	21.9	119,507

we show that our findings remain robust even when we restrict the sample to the Northeast, a region with a denser network of gauge stations.

Second, the average monthly rent in the inundated zip codes is \$1,702, which is over \$400 higher than the average rent in all other zip codes in the ZORI dataset.[18] The difference in the rental rates (at least partly) reflects the amenity value of being closer to the ocean. In addition to the large spillover effects reported in Section 4, the level difference in rental rates suggests that zip codes outside of the inundation map might not be a good control group. Thus our empirical exercise leverages variations in HTF occurrences among inundated zip codes.

Third, the number of days with HTF in the past 12 months is an order of magnitude larger than that of moderate or major floods. Also, the difference between the mean (5.6) and median (5) number of days with HTF suggests that the average number of days with HTF is unlikely to be driven by a few extreme values. Finally, the average community files 0.8 NFIP claims per month from floods of all sizes. We use NFIP claims to investigate direct damage caused by HTF.

4 High Tide Flooding and Impaired Mobility

Estimation framework. Individuals undertake trips because such visits contribute positively to their utility. When external factors, such as floods, prevent individuals from making these trips, their utility diminishes. Building on this premise, this section examines whether $U_D(z, x) > U_F(z, x)$ by

[18] There are 7,042 zip codes in the ZORI data and 1,471 of them have an overlap with the NOAA inundation map.

analyzing the negative impact of HTF on mobility using a distributed lag model in equation (3).

$$log(Visits_{zdt}) = \sum_{j \in [-10,10], j \neq -1} \beta_j F_{zt,d-j} + \alpha_{zm} + \lambda_{dt} + \theta_{ct} + \epsilon_{zdt} \quad (3)$$

Here $Visits_{zdt}$ denotes the number of visits to zip code z on date d in year t (e.g., Jan 1, 2019). $F_{zt,d-j}$ are a set of indicators for 10 leads and 10 lags around the HTF event (i.e., $j \in \{-10, -9, \ldots, 9, 10\}$) in zip code z. For leads larger than 10 (e.g., 11), we impose end-point restrictions to 10. We include zip code by calendar month fixed effects, α_{zm}, to control for zip code specific seasonality. We also include county by year fixed effects, θ_{ct}, to control for local economic shocks that might affect visits. Finally, λ_{dt} denotes date-year fixed effects, which absorb any shocks common to all zip codes on a given day including holidays, weekends, and lunar phases.

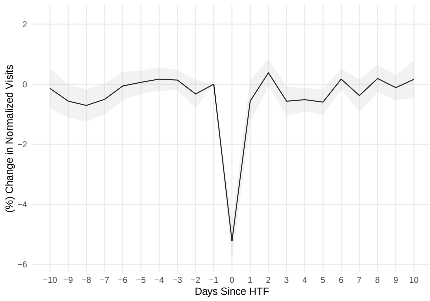
The coefficient of interest is β_j, the effect of HTF on the number of visits for j relative to $j = -1$. Since the occurrence of HTF on a particular day is governed by a plausibly random physical processes, our preferred specification does not include additional control variables. Nevertheless, we demonstrate that the results remain highly stable across a range of alternative specifications. Throughout the analysis, standard errors are clustered at the county level. To prevent composition changes, we use the identical set of zip codes as Section 5 for our main analysis.

Results. Figure 4.1 illustrates the impact of HTF on the number of visits.[19] Panel (a) shows that on the day of HTF, the number of visits decreases by 5% compared to the previous day. Importantly, this 5% likely underestimates the true impact of HTF on mobility, as it reflects only the extensive margin. That is, while some individuals may still complete their trips—albeit via longer routes or slower travel with higher time costs—such adjustments are not captured in Panel (a).[20]

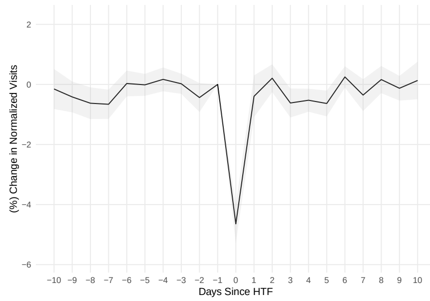
Panels (b)-(f) show that results in Panel (a) remain robust to a series of alternative specifications. Specifically, we (b) control for zip code level concurrent weather conditions—precipitation, moderate and major flood events; (c) control for 10-day leads and lags of precipitation as well as moderate and major flood events; (d) drop observations with leads greater than 10 (instead of binning endpoints);

[19] Appendix Table A.2 and A.3 present coefficients appear in Figure 4.1 (a)-(f) and (g)-(i), respectively.

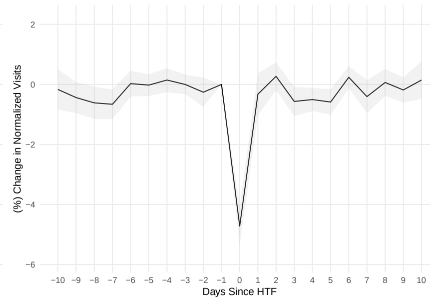
[20] There is limited data on the increased time effect due to HTF but a back-of-the-envelope calculation suggests that each HTF is likely to cause a non-trivial increase in travel time. For instance, take the annual HTF-induced additional driving time per vehicle (2 hours) from Jacobs et al. (2018) and divide it by the average number of HTF per year (5.6). This means that on the day of HTF, it takes 21 more minutes to travel. In dollar terms, this amounts to \$7.8 based on the value of time estimate from Goldszmidt et al. (2020) (\$22.15 in 2021 dollar).



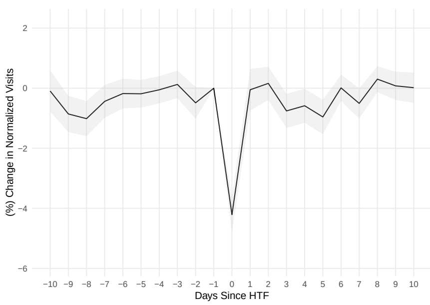
(a) Main Specification



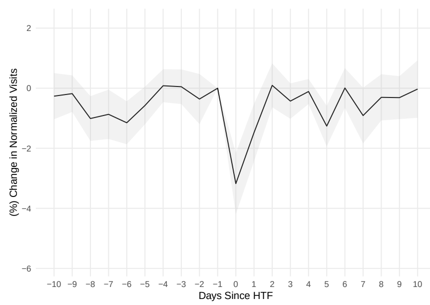
(b) Weather Controls



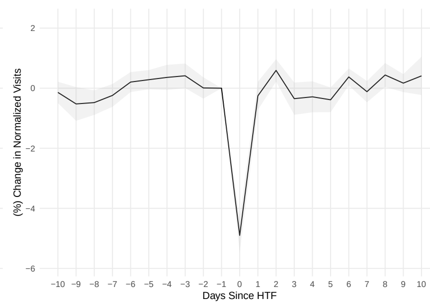
(c) Precipitation Leads/Lags



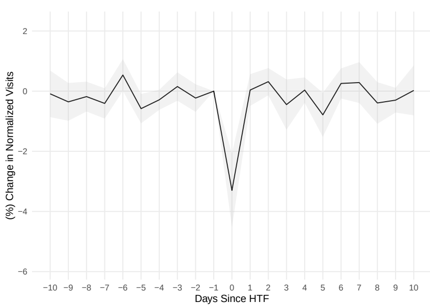
(d) No Endpoint Binning



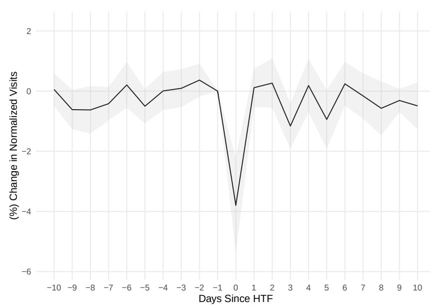
(e) Areas with Denser Gauge Networks



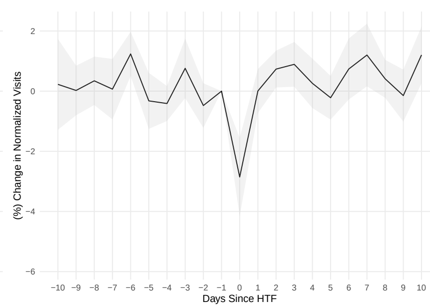
(f) Normalized Visits



(g) Spillover



(h) Spillover - Low Resiliency



(i) Spillover - High Resiliency

Figure 4.1: The Effects of HTF on Daily Visits. These plots show the impact of HTF on the number of visits in the 10 days before and after an event, estimated under various specifications. Panel (a) presents results from our main specification. Panel (b) adds controls for daily weather conditions, while panel (c) further includes leads and lags of precipitation. Panel (d) drops observations with leads larger than 10 (instead of binning endpoints). Panel (e) restricts the sample to zip codes within the 10 Northeast states. Panel (f) uses the normalized number of visits to account for variation in sampling rates. Panel (g) examines the impact on adjacent but not inundated zip codes to detect spillover effects, while panels (h) and (i) explore how the size of these spillover effects varies with the resiliency of local road networks. In all panels, the outcome variable is the log of visits to all destinations. Grey areas show the 95% confidence interval.

(e) restrict the analysis to 10 Northeast states with a denser network of gauge stations;[21] and (f) normalize the number of visits to account for varying sampling rates over time.[22] The consistency of estimates suggests that our identification is not sensitive to modeling choices, strengthening the plausibility of causal interpretation.

Next, we examine potential spillover effects to assess whether Panel (a) overstates the true impact on mobility by overlooking possible displacement to nearby non-inundated (dry) areas. Theoretically, the effect of HTF on visits to dry zip codes is ambiguous. In a resilient road network—one that can absorb disturbances and maintain functionality (Wan et al. 2018)—trips between dry areas are unlikely to be significantly disrupted. Moreover, some trips originally planned from dry areas to inundated locations may be redirected to alternative dry destinations, which could result in an increase in visits to nearby non-inundated zip codes. Conversely, in regions with less resilient road networks, HTF-related disruptions may propagate across the broader transportation system, generating network-wide congestion. Under such conditions, increased travel times may not only limit the scope for substitution but also reduce travel between dry areas.

To empirically test this, we estimate equation (3) on zip codes that do not overlap with the NOAA inundation map but are (1) located within 30 miles of the coastline and (2) included in the Zillow dataset. Panel (g) indicates that the number of trips to these zip codes declines by 3% (60% of effects in Panel (a)) on the day of HTF, suggesting that the scope of such substitution is limited, and system-wide disruptions are prevalent. This finding aligns with transportation studies literature, which shows that the closure of even a small share of road segments in US cities can trigger region-wide travel delays (Kasmalkar et al. 2020, Hauer et al. 2021, Rajput et al. 2023).

To investigate why spillover effects in Panel (g) arise, Panels (h) and (i) test whether magnitude of trip reduction varies with road network resiliency, consistent with earlier theoretical predictions. Specifically, we classify metropolitan areas into relatively high- and low-resiliency groups based on the rank-ordering of metropolitan areas by road network resilience from Ganin et al. (2017), and estimate equation (3) separately for each group.[23] The results show that the spillover effect is notably

[21] These 10 states are CT, DC, DE, MA, MD, ME, NJ, NY, RI, and VA.

[22] Sampling rate (i.e., the number of devices included in the Safegraph data out of the total number of devices in the US) has changed substantially over time (Kurmann and Lalé 2022). In Panel (f), we build on Kurmann and Lalé (2022) and divide raw visit counts by the number of unique mobile devices for each zip code-month.

[23] Ganin et al. (2017) estimate the increase in travel delays resulting from a 5% random loss of road linkages across 40 US metropolitan areas. We use their resilience rankings to classify the 17 metros in our sample into high- and low-resiliency groups. High-resiliency areas in our sample are Philadelphia (PA), Baltimore (MD), Richmond (VA), Miami

smaller in areas with more resilient networks—about 50% of Panel (a)—compared to approximately 70% in low-resiliency areas. This variation in effect size not only lends support for the theoretical prediction, but also reassures that the spillover effect is not driven by spurious correlations or unobserved confounding.

In Appendix Figure A.4, we turn our attention to category specific effects to further investigate the source of utility losses from flood events. Panels (a)-(e) reveal that HTF significantly disrupts access to essential infrastructures—hospitals, school, childcare facilities, and various retail stores—as well as workplaces.[24] This suggests that the cost of HTF extends far beyond a minor nuisance, potentially leading to losses in health, learning, access to essential goods like food, and productivity and income. Further, Panels (f) and (g) show that HTF restricts access to key local amenities—accommodation and food services, and recreation destinations—which causes loss of leisure. Importantly, the breadth of affected categories implies that the potential for adaptation is limited even for most insulated individuals in society. For instance, HTF is likely to negatively affect the productivity of remote workers if, for instance, they have young children and access to daycare is restricted.

It is worth highlighting that the number of visits one or two days before HTF does not exceed other days in any of the categories including the most flexible destinations like retail shops. Such a lack of anticipatory behavior starkly contrasts with responses to extreme temperatures or natural disasters, where households typically make preemptive trips in advance to fulfill their needs while avoiding travel during the negative shock (Beatty et al. 2019, Li and Mostafavi 2022, Lee and Zheng 2025b). This difference is likely attributable to the fact that, while forecasts for natural disasters or extreme temperatures are readily available, comparable predictive services for HTF remain scarce (Dusek et al. 2022).[25] Furthermore, the absence of a rebound effect post-HTF suggests that the HTF reduces rather than postpones activities.

(FL), Los Angeles (CA), San Diego (CA), Sacramento (CA), and Seattle (WA). Low-resiliency areas are Boston (MA), Providence (RI), Washington (DC), Orlando (FL), Jacksonville (FL), Tampa (FL), Houston (TX), San Francisco (CA), and San Jose (CA).

[24] We analyze category specific effects using visits to the following NAICS codes: hospital (621), childcare facilities (6244), retail stores (44 and 45), accommodation and food services (72), and recreation destinations (71). For workplaces, we combine 14 work-related places with two-digit NAICS codes 48, 52, 92, 51, 54-56, 23, 31-33, 42, 49, and 22. For more details, see Appendix Table A.1 and https://www.naics.com/search.

[25] While tidal predictions have been available for decades, HTF forecasts have only emerged recently. NOAA's Monthly High Tide Flooding Outlook, introduced in August 2023 as part of the Bipartisan Infrastructure Law (NOAA 2023), marks the first formal effort to provide proactive HTF forecasts. The National Weather Service also issues coastal flood advisories and warnings, but these are typically released shortly before an event, offering limited time for individuals or communities to adjust their behavior in advance.

In Panel (h), we examine the impact of HTF on visits to auto repair shops to assess potential effects on physical assets. We find no evidence of an increase in repair activity following HTF events. Instead, the cumulative 10-day effect on visits ($\sum_{j=0}^{10} \beta_j$) is –4.1%, indicating that the net impact remains negative despite a modest rebound in visits after the event.

5 Effect of High Tide Flooding on Rental Rates

Estimation framework. Results in Section 4 provide the "first-stage" evidence that HTF substantially disrupts daily life, namely $U_D > U_F$. This section aims to quantify $U_D - U_F$, the economic cost of floods. For this, we investigate the impact of HTF on rental rates using equation (4).

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

Here Y_{czmt} is the average monthly rent for zip code z in county c in month m at year t. We include a rich set of fixed effects. Zip code fixed effects α_z control for time-invariant zip code level characteristics including amenity level (e.g., distance to the ocean). 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. θ_m accounts for seasonality. The key independent variable is N_{zmt}, the number of days with HTF in the past 12 months for a zip code z at time mt, which proxies for p in equation (2). Per equation (2), β represents the MWTP to avoid a marginal increase in HTF exposure, which can also be interpreted as a lower bound economic cost of flooding per day. As detailed in Section 3.1, our identification strategy relies on plausibly random year-to-year variation in local HTF occurrences, which provides strong identification properties.

Results. Table 5.1 column (1) reports that one additional day of HTF in the past 12 months reduces rent by 0.24%. When evaluated at the annual mean rent, which corresponds to r equation (2), this amounts to a \$48 reduction.[26] Importantly, equation (2) indicates that \$48 is MWTP to avoid exposure to HTF or a lower bound economic cost of flooding, which reflects a range of financial and non-financial impacts of HTF as documented in Appendix Figure A.4.[27] Given that the average num-

[26] r represents the total payment over the rental period. Since over 60% of lease terms are 12 months, a natural empirical analog of r is 12 times the monthly rent (Houck 2022).

[27] The result in column (1) might be implausible if the majority of renters are not aware of HTF, potentially due to being new residents in the area. However, the Survey of Income and Program Participation panel data, which has

ber of days with HTF in the sample is 5.6, the estimated coefficient suggests a 1.3% or $269 decline in annual rent per unit.[28] Our estimated effect is smaller than Benetton et al. (2022), who finds that rental prices in Venice increase by 6% (or 0.65% per day of tidal flooding) following the construction of a sea wall, which protects properties from tidal flooding and improves the quality of life.

As discussed in Section 2, interpreting $48 as the economic cost of floods relies on the assumption that HTF affects rental rates only through expectation. We provide two pieces of evidence in support of this. First, in column (2), we estimate the impact of HTF on the number of flood insurance claims to test whether the impact of HTF on rent is partly attributable to direct damage. Because a flood insurance claim has to be made within 60 days of damage (FEMA 2016), we use the number of days with HTF in the past two months as our key regressor. The result indicates that HTF rarely incurs direct damage: one additional day of HTF in the past two months has no statistically significant increase in the number of flood insurance claims. Moreover, even if HTF incurs minor damage, it is unlikely to affect renters directly, as such risks are typically borne by landlords.

Second, in Appendix Figure A.5, we test whether HTF affects rental prices by degrading local amenities—for example, through lasting impacts on parks or recreational areas. For this, we extend the exercise from Section 4 using longer lags. Our results suggest that the number of visits to these amenities returns to normal levels quickly after an HTF and remains stable over the subsequent 30 days. Drawing on insights from the recreational demand model, we interpret this as evidence that HTFs do not inflict significant long-term damage on local amenities (Phaneuf and Smith 2005).

In columns (3)-(5), we use alternative measures for belief on the likelihood of HTF during rental periods (p from equation (2)). Specifically, column (3) allows belief formation based on further past—past 24 months as opposed to 12 months—and find that the result is very similar to column (1). In column (4), we retain N_{zmt} in equation (4) but include three lags (the number of days with HTF in the past 13-24, 25-36, and 37-48 months) as additional regressors. This specification allows beliefs to be shaped not only by the most recent exposure but also by longer-term historical experience.[29] The finding suggests that results in column (1) could be a conservative estimate of an economic cost.

been frequently used to study the duration of residence (Mateyka and Marlay 2010), suggests that the median (mean) duration of tenancy for renters in coastal states is 36 (64) months as of 2018, which implies that renters likely possess or acquire local knowledge.

[28]The estimated effect may underestimate the true impact on rental prices if landlords offer non-monetary concessions (e.g., renovating bathrooms or replacing appliances) instead of reducing rents.

[29]To make the model saturated, we drop about 1% of observations that had no HTF over the sample period.

Table 5.1: Effect of High Tide Flooding on Rental Rates and Flood Insurance Claims

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Var.:	log(Rent)	Claim Ct	log(Rent)	log(Rent)	log(Rent)	log(Rent)	log(Rent)	log(Rent)
HTF Days (Past 12 Months)	-0.0024***			-0.0036***		-0.0015***	0.0002	-0.0025***
	(0.0004)			(0.0008)		(0.0003)	(0.0008)	(0.0005)
HTF Days (Past 2 Months)		0.0891						
		(0.1106)						
HTF Days (Past 24 Months)			-0.0022***					
			(0.0005)					
HTF Days (Past 13-24 Months)				-0.0026**				
				(0.0012)				
HTF Days (Past 25-36 Months)				-0.0019				
				(0.0013)				
HTF Days (Past 37-48 Months)				-0.0014				
				(0.0010)				
HTF Days (Forecast)					-0.0030			
					(0.0029)			
Sample	Main	Main	Main	Main	2018–21	No Inund Low Resilient	No Inund High Resilient	Northeast
Zip Code	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Year-County	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	119,507	119,507	119,507	117,061	5,810	34,712	46,388	75,455

Note:
Column (1) present the impact of having one additional day of HTF in the past 12 months—a measure of renters' belief on the number of HTF during rental periods—on log of rental rates. Column (2) shows the impact of having one additional day of HTF in the past 2 months (claims window) on the number of flood insurance claims. Columns (3)-(5) show results from alternative belief measures. Columns (6) and (7) repeat column (1) using non-inundated coastal zip codes with low- and high- road network resiliency, respectively. Column (8) repeat column (1) using zip codes that are in the 10 Northeast states. Standard errors are clustered at the county level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

In column (5), we assume individuals are sophisticated, forming expectations based on scientific forecasts rather than relying on past events. For the source of these scientific forecasts, we use NOAA's HTF annual outlook data series, which is reported annually for 2018–21.[30] Thus, we aggregate the rent data to the same temporal resolution and regress it on the forecasted number of days with HTF. The resulting coefficient is underpowered, but the point estimate is similar—albeit somewhat larger—to the rest of the columns at -0.3%. Collectively, these results suggest that the belief measure in column (1) is robust to alternative assumptions about belief formation.

Mobility results in Figure 4.1 (g)–(i) suggest that even when a zip code is not directly inundated by HTF, the utility of residing in that location can still decline due to spillover effects, particularly in areas with less resilient road networks. In Columns (6) and (7), we test whether these mobility spillovers translate into housing market outcomes by estimating the impact of HTF on rental rates in metropolitan areas with high and low road network resiliency. The analysis focuses on zip codes located within 30 miles of the coastline but outside the inundation map. We find that the negative impact of HTF on rental rates appears only in zip codes within low-resiliency areas, suggesting that impaired mobility is a key channel through which HTF events affect local housing markets.

Finally, in column (8), we test if potential errors in HTF measurement affect our results. For this, we estimate equation (4) only for zip codes in the 10 Northeast states that have a denser network of gauge stations, and report that the estimated effect is essentially identical to column (1).

We conduct two additional robustness checks: we repeat the same exercise as Table 5.1 with control variables (Appendix Table A.4) and with the county by month—as opposed to month—fixed effects (Appendix Table A.5), which, for instance, allow for county specific seasonality in the housing market. The results are strikingly stable for rental rates. In contrast, the estimates for flood insurance claims vary in direction across specifications and lack economic and statistical significance, reinforcing the conclusion that HTF exposure has minimal impact on asset losses.

In Figure 5.1, we non-parametrically estimate the impact of HTF on rental rates. For this, we create a saturated set of "dose" indicators that take 1 when the number of days with HTF in the past 12 months for a zip code in a given year-month is in bin k where $k \in \{0, 1, 2, \cdots, 19, 20+\}$. Because we use $k = 0$ as the baseline category, the estimated coefficients for each bin indicate the additional rental rate impact when a zip code experiences k days of HTF as opposed to 0.

[30] These reports are downloaded from https://tidesandcurrents.noaa.gov/pub.html#htf (accessed Dec 23, 2024).

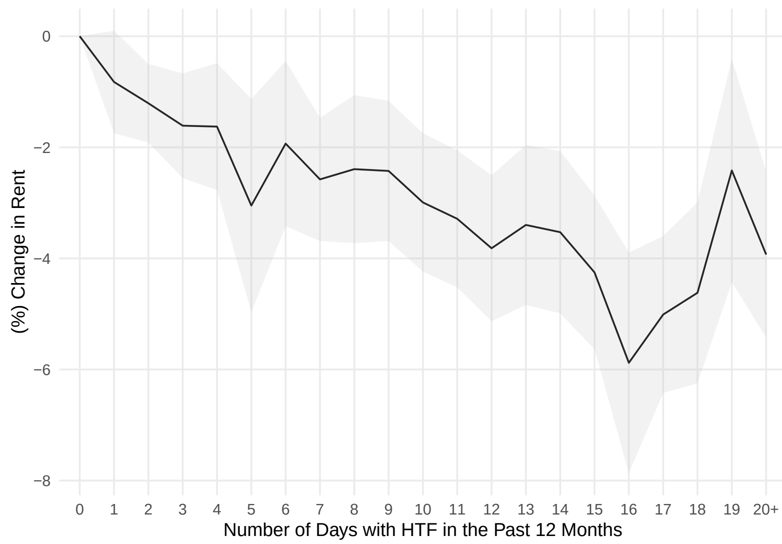


Figure 5.1: The Impact of HTF on Rental Rates by Frequency. This plot shows how the impact of HTF on rental rates varies by the frequency of HTF incidents. For this, we regress HTF exposure bins (e.g., 2 indicates that a zip code had 2 days of HTF exposure in the past 12 months) on the log of rent. Shaded area represents the 95% confidence interval.

The estimated coefficients in Figure 5.1 show that rental rates nearly monotonically decrease as exposure increases. For instance, while having 1 day with HTF reduces rental rates by 0.7%, having 10 days with HTF affects rental rates by over 3%. More generally, the curvature indicates that a linear parameterization in Table 5.1 column (1) is a reasonable first-order approximation.

Further, estimates in Figure 5.1 can be used for additional robustness checks. Callaway et al. (2024) shows that equation (4) may suffer selection bias in the presence of a heterogeneous treatment effect. To explore to what extent this issue might bias our estimates, we follow Callaway et al. (2024) and calculate the MWTP parameter using a frequency-weighted average of first-differenced non-parametric estimates, namely $\sum_{k=1}^{20}(\beta^k - \beta^{k-1})P(N = n_k|N > 0)$ where β^k is the estimated effect for bin k and N is the number of days with HTF in the past 12 months. We find that this procedure implies that MWTP to avoid one additional day of HTF is 0.0031 (s.e. = 0.0005) or 0.31%, which is consistent with the results in Table 5.1 column (1).

6 Discussion

In this section, we calculate the economic cost of large floods using the Presidential Disaster Declaration (PDD) floods as examples. As previously discussed, we interpret the 0.24% (or \$48) reduction in rent from Table 5.1, Column (1), as a daily, per-household lower bound estimate of the economic cost of flooding, capturing impacts that extend beyond direct asset losses.[31] With this caveat, we multiply \$48 by the number of households exposed to the PDD floods and by each event's duration.

One potential approach to identify the number of households exposed to PDD is using readily available location information (county) in FEMA's PDD database.[32] However, flood damage can be highly localized and some parts of a county might not be affected by the event. Thus, we estimate zip code specific mobility impact due to a PDD to identify the number of households affected by the event. For this, we first list up zip codes that are located within the counties affected by each PDD. Then, for each zip code, we estimate equation (5), which compares the number of visits for PDD periods ($PDD_{dt} = 1$ when a day has PDD or is within three lags) to the rest of days in the 2018–21 period after controlling for daily precipitation, month, day of the week (e.g., Monday), and year fixed effects. The coefficient of interest is β_z, which represents zip code specific mobility impact due to a PDD event. We cluster standard errors at the fortnightly level to account for potential serial correlation in the error.

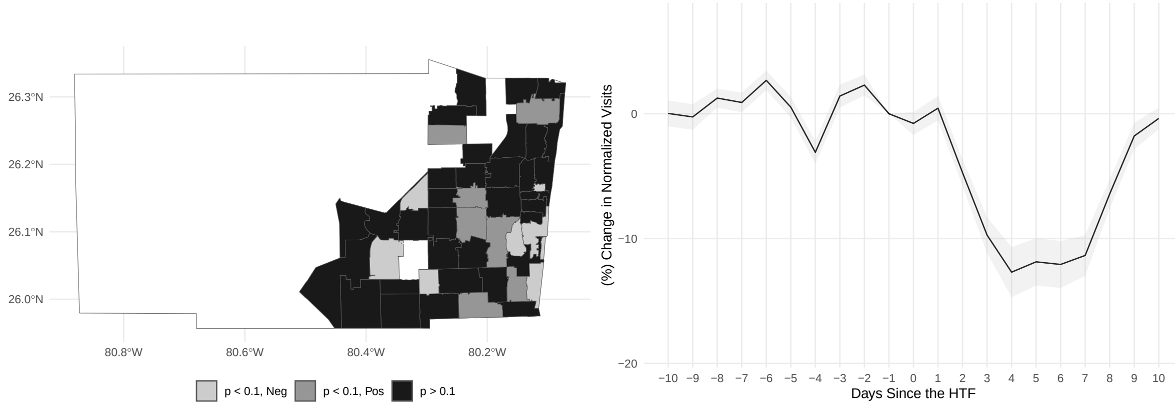
$$log(Visits_{dt}) = \beta_z PDD_{dt} + \gamma \mathbf{X}_{dt} + \alpha_m + \lambda_w + \theta_t + \epsilon_{dt} \tag{5}$$

Figure 6.1 (a) illustrates the value of this approach.[33] Here, we classify zip codes into three categories: those with statistically significant (at the 90% confidence level) negative impacts, statistically significant but positive impacts, and statistically insignificant impacts. Importantly, to prevent over-estimation, we only treat households in the first group, which are 7 out of 47 zip codes in Figure 6.1 (a), as zip codes that are negatively affected by PDD. More generally, we find that 30% of zip codes that are included in PDD counties over the 2018–21 period are negatively and statistically significantly affected by PDD events. Given that zip codes in the other two categories could be still negatively affected by PDD events, we believe this is a conservative estimate. Using the number of households information from the American Community Survey, we find that for a typical year, 12.4 million households are residing in zip codes that are affected by PDD floods over this period.

[31] 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 economic cost estimate will lie between the vertical and flat MWTP curve cases.

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

[33] The large blank in Figure 6.1 (a) is the Everglades and Francis S. Taylor Wildlife Management Area.



(a) Zip Code Specific Impact from Broward County, FL

(b) Impact for PDDs with 7+ days of Incident Window

Figure 6.1: The Mobility Impact of PDD Floods. Panel (a) illustrates zip code specific PDD flood impact on the number of visits for Broward county, FL. Panel (b) shows the mobility impact over time for PDDs with documented incident window of 7+ days.

For the duration of an event, we leverage the "incident window" in the PDD dataset after making a few adjustments. Because the incident window, whose primary purpose is establishing the eligibility window for federal assistance (Lee et al. 2023), may not correspond to the actual physical flood duration, we first cap the incident window at seven days to prevent overstating the duration. Further, we compare the incident window to an empirical flood duration, which we estimate using the mobility data similar to our exercise in Section 4. For this, we separately estimate equation (3) for PDD events with documented "incident window" of 1–2, 3–4, 5–6, and 7+ days, and examine the number of days with statistically significant negative mobility impacts. Figure 6.1 (b) illustrates the impact of PDD floods with the documented duration of 7+ days. We find that the negative mobility impact lasts for over 10 days, which is longer than the documented incident window. Similarly, in Appendix Figure A.6 we present results for all incident window categories, which show that the incident window does not seem to overestimate the actual flood duration.

By multiplying \$48 to the number of affected households and duration of each PDD, we find that the annual economic cost of PDD over 2018–21 is at least \$4 billion. We highlight that \$4 billion is a lower bound because (1) the economic costs of PDD floods are much larger than HTF as evidenced by Figure 6.1 (b)—the impact of PDD on the number of trips is more than twice larger than that of HTF—and (2) PDDs typically cause severe asset losses which further reduces the utility level.

To benchmark, we compare \$4 billion to the sum of flood insurance claims and federal disaster relief funds attributed to these PDD floods, which amounts to $5 billion. Similar to our findings, Benetton et al. (2022) shows that housing prices for ground-floor units—susceptible to both asset losses and economic costs from floods—increase by 7% following the construction of a sea wall, while prices for higher-floor units, which experience economic costs alone, rise by 4%. Hallegatte (2008) and Koks et al. (2015) also find that indirect economic costs can be larger than direct losses.

While actual asset losses are likely higher than $5 billion due to limits on payouts—such as caps on insurance coverage or disaster relief amounts—this comparison suggests that ignoring the economic costs can substantially underestimate the true flood cost, which in turn can undermine the accuracy of cost-benefit analyses of flood policies (National Science and Technology Council 2023).

7 Conclusion

While the theoretically consistent cost of floods is a welfare loss from the event, existing cost estimates are predominantly based on asset losses due to measurement challenges. In this paper, we leverage variations in HTF, a highly disruptive yet rarely destructive flood event, to estimate the economic cost of floods that goes beyond the asset losses.

Using mobile phone based high-frequency trip data, we find direct evidence that HTF disrupts local mobility. On the day of an event, the number of visits declines by 5% in inundated zip codes, and these disruptive effects often spill over into adjacent—but not directly inundated—areas, particularly in cities with less resilient road networks. Further, by disaggregating the impacts by destination type, we show that HTF disrupts access to a broad range of locations, including essential infrastructure, urban amenities, and workplaces. This suggests that the cost of inundation due to floods extends far beyond a nuisance, potentially leading to losses in health, learning, leisure, access to essential goods like food, and productivity and income. Then, using zip code level rental rates data, we show that being exposed to one additional day of HTF in the past 12 months, which proxies for renters' expectations about flooding during their lease period, reduces rents by 0.24% or $48 per day. Given the disruptive nature of HTF, we interpret this as the economic cost of floods.

Using this parameter as a lower bound of economic cost from large floods, we show that annual economic costs from PDD floods over the 2018–21 period is at least $4 billion. Our findings suggest that ignoring costs beyond asset losses can substantially underestimate the true cost of floods. This parameter holds significant practical implications, particularly given the federal government's efforts to enhance cost-benefit analyses by incorporating currently non-monetized costs of natural disasters (National Science and Technology Council 2023).

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A Additional Tables and Figures

Table A.1: Relative Frequency by NAICS Categories in the SafeGraph Patterns Data

Category	NAICS Code	Pct. of Visit Counts	Pct. of Places
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 relative frequency of places by NAICS industry codes in the SafeGraph Patterns data.

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Table A.2: Effect of High Tide Flooding on Mobility

	(1)	(2)	(3)	(4)	(5)	(6)
Lead 8	-0.0071**	-0.0063**	-0.0061**	-0.0101***	-0.0101***	-0.0048**
	(0.0028)	(0.0027)	(0.0028)	(0.0030)	(0.0038)	(0.0021)
Lead 7	-0.0050*	-0.0066***	-0.0066***	-0.0044	-0.0087**	-0.0024
	(0.0026)	(0.0025)	(0.0025)	(0.0028)	(0.0042)	(0.0019)
Lead 6	-0.0006	0.0003	0.0003	-0.0018	-0.0115***	0.0021
	(0.0024)	(0.0022)	(0.0022)	(0.0025)	(0.0036)	(0.0017)
Lead 5	0.0006	-0.0001	-0.0002	-0.0019	-0.0058*	0.0028*
	(0.0020)	(0.0019)	(0.0018)	(0.0024)	(0.0032)	(0.0016)
Lead 4	0.0017	0.0017	0.0015	-0.0005	0.0008	0.0036*
	(0.0020)	(0.0020)	(0.0020)	(0.0023)	(0.0028)	(0.0021)
Lead 3	0.0014	0.0002	-5.65e-6	0.0013	0.0005	0.0041**
	(0.0017)	(0.0017)	(0.0017)	(0.0023)	(0.0029)	(0.0021)
Lead 2	-0.0033	-0.0044*	-0.0026	-0.0049*	-0.0036	8.87e-5
	(0.0024)	(0.0025)	(0.0025)	(0.0027)	(0.0043)	(0.0018)
HTF	-0.0522***	-0.0464***	-0.0472***	-0.0421***	-0.0318***	-0.0490***
	(0.0033)	(0.0033)	(0.0033)	(0.0030)	(0.0052)	(0.0028)
Lag 1	-0.0056	-0.0040	-0.0032	-0.0005	-0.0148***	-0.0025
	(0.0035)	(0.0035)	(0.0035)	(0.0035)	(0.0049)	(0.0024)
Lag 2	0.0038	0.0021	0.0027	0.0016	0.0010	0.0059***
	(0.0024)	(0.0024)	(0.0024)	(0.0028)	(0.0037)	(0.0019)
Lag 3	-0.0057**	-0.0062**	-0.0057**	-0.0076***	-0.0043	-0.0035
	(0.0025)	(0.0025)	(0.0025)	(0.0029)	(0.0030)	(0.0027)
Lag 4	-0.0052***	-0.0053***	-0.0050**	-0.0058**	-0.0011	-0.0029
	(0.0020)	(0.0020)	(0.0020)	(0.0029)	(0.0021)	(0.0026)
Lag 5	-0.0060***	-0.0063***	-0.0059***	-0.0096***	-0.0126***	-0.0039*
	(0.0022)	(0.0022)	(0.0022)	(0.0029)	(0.0034)	(0.0021)
Lag 6	0.0017	0.0025	0.0024	0.0001	7.49e-5	0.0038***
	(0.0018)	(0.0018)	(0.0019)	(0.0022)	(0.0034)	(0.0014)
Lag 7	-0.0038	-0.0035	-0.0041	-0.0051*	-0.0091*	-0.0012
	(0.0027)	(0.0027)	(0.0028)	(0.0026)	(0.0047)	(0.0018)
Lag 8	0.0019	0.0016	0.0007	0.0030	-0.0030	0.0044**
	(0.0023)	(0.0023)	(0.0023)	(0.0022)	(0.0039)	(0.0020)
Model	Main	Weather Ctrl	Rain Lead/Lag	No Binning	Northeast	Normalized
Observations	2,096,685	2,096,685	2,095,310	412,167	727,024	2,096,685

Note:
This table corresponds to Figures 4.1 (a)-(f). For the interest of space, only 8 leads and lags are presented. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

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Table A.3: Effect of High Tide Flooding on Mobility (Not Inundated Zip Codes)

	(1)	(2)	(3)
Lead 8	-0.0018	-0.0062	0.0034
	(0.0025)	(0.0040)	(0.0041)
Lead 7	-0.0041	-0.0042	0.0007
	(0.0026)	(0.0028)	(0.0051)
Lead 6	0.0054**	0.0021	0.0124***
	(0.0027)	(0.0039)	(0.0037)
Lead 5	-0.0058**	-0.0050*	-0.0032
	(0.0025)	(0.0029)	(0.0048)
Lead 4	-0.0029*	7.48e-5	-0.0041
	(0.0017)	(0.0032)	(0.0030)
Lead 3	0.0015	0.0009	0.0076
	(0.0024)	(0.0032)	(0.0050)
Lead 2	-0.0023	0.0037	-0.0048
	(0.0023)	(0.0028)	(0.0038)
HTF	-0.0330***	-0.0380***	-0.0285***
	(0.0063)	(0.0082)	(0.0066)
Lag 1	0.0004	0.0011	5.93e-5
	(0.0027)	(0.0032)	(0.0037)
Lag 2	0.0032	0.0027	0.0073**
	(0.0023)	(0.0042)	(0.0031)
Lag 3	-0.0045	-0.0116***	0.0089**
	(0.0043)	(0.0039)	(0.0038)
Lag 4	0.0004	0.0019	0.0026
	(0.0021)	(0.0045)	(0.0042)
Lag 5	-0.0079**	-0.0094*	-0.0022
	(0.0037)	(0.0050)	(0.0037)
Lag 6	0.0026	0.0024	0.0074
	(0.0025)	(0.0037)	(0.0052)
Lag 7	0.0028	-0.0016	0.0120**
	(0.0035)	(0.0038)	(0.0053)
Lag 8	-0.0039	-0.0057	0.0041
	(0.0035)	(0.0046)	(0.0032)
Sample	No Inund	No Inund Low Resilience	No Inund High Resilience
Observations	1,398,909	593,930	804,979

Note:
This table corresponds to Figures 4.1 (g)-(i). For the interest of space, only 8 leads and lags are presented.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

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Table A.4: Effect of High Tide Flooding on Rental Rates and Flood Insurance Claims (with Controls)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Var.:	log(Rent)	Claim Ct	log(Rent)	log(Rent)	log(Rent)	log(Rent)	log(Rent)	log(Rent)
HTF Days (Past 12 Months)	-0.0024***			-0.0036***		-0.0015***	0.0002	-0.0024***
	(0.0004)			(0.0008)		(0.0003)	(0.0008)	(0.0004)
HTF Days (Past 2 Months)		-0.1599						
		(0.1378)						
HTF Days (Past 24 Months)			-0.0022***					
			(0.0005)					
HTF Days (Past 13-24 Months)				-0.0025**				
				(0.0012)				
HTF Days (Past 25-36 Months)				-0.0019				
				(0.0013)				
HTF Days (Past 37-48 Months)				-0.0014				
				(0.0010)				
HTF Days (Forecast)					-0.0029			
					(0.0027)			
Sample	Main	Main	Main	Main	2018–21	No Inund Low Resilient	No Inund High Resilient	Northeast
Zip Code	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Year-County	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	119,493	119,493	119,493	117,047	5,810	33,789	46,388	47,202

Note:
This table reproduces Table 5.1 by including zip code level control variables: monthly precipitation, the number of days with larger floods in the past 12 months (past 2 months for column (2) and past 24 months for column (3)), median income, share of rental units, share of population with college degree, and share of minority population. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.5: Effect of High Tide Flooding on Rental Rates and Flood Insurance Claims (Alt. FE)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Var.:	log(Rent)	Claim Ct	log(Rent)	log(Rent)	log(Rent)	log(Rent)	log(Rent)
HTF Days (Past 12 Months)	-0.0023***			-0.0036***	-0.0015***	0.0002	-0.0025***
	(0.0004)			(0.0009)	(0.0003)	(0.0008)	(0.0005)
HTF Days (Past 2 Months)		0.0294					
		(0.1015)					
HTF Days (Past 24 Months)			-0.0022***				
			(0.0006)				
HTF Days (Past 13-24 Months)				-0.0025*			
				(0.0014)			
HTF Days (Past 25-36 Months)				-0.0018			
				(0.0015)			
HTF Days (Past 37-48 Months)				-0.0013			
				(0.0011)			
Sample	Main	Main	Main	Main	No Inund Low Resilient	No Inund High Resilient	Northeast
Zip Code	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-County	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-County	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	119,507	119,507	119,507	117,061	34,712	46,388	75,455

Note:
This table reproduces Table 5.1 by including month by county fixed effects as opposed to month fixed effects. Note, column (5) from Table 5.1 is excluded because observations are at the annual level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

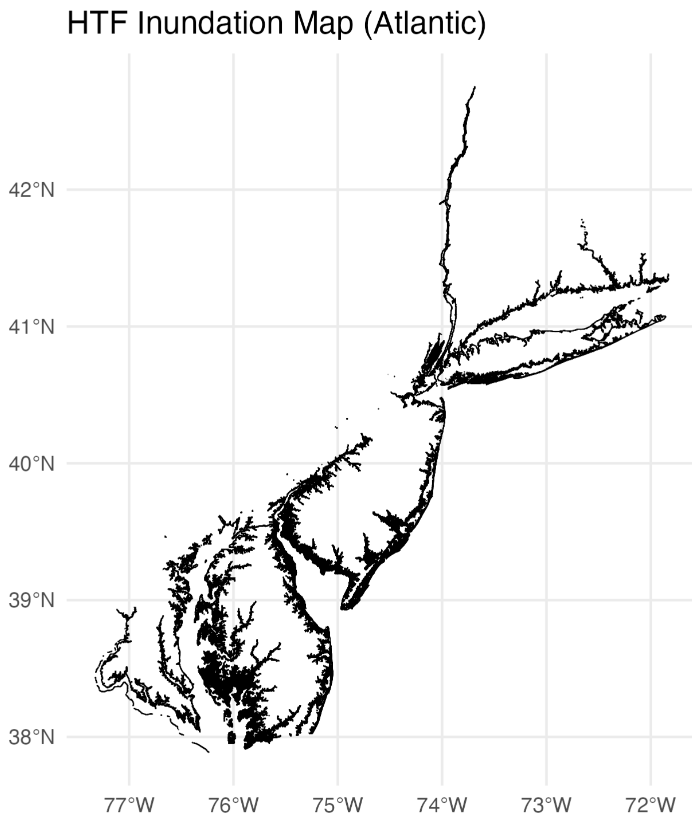

Figure A.1: Inundation Map (Atlantic Region)

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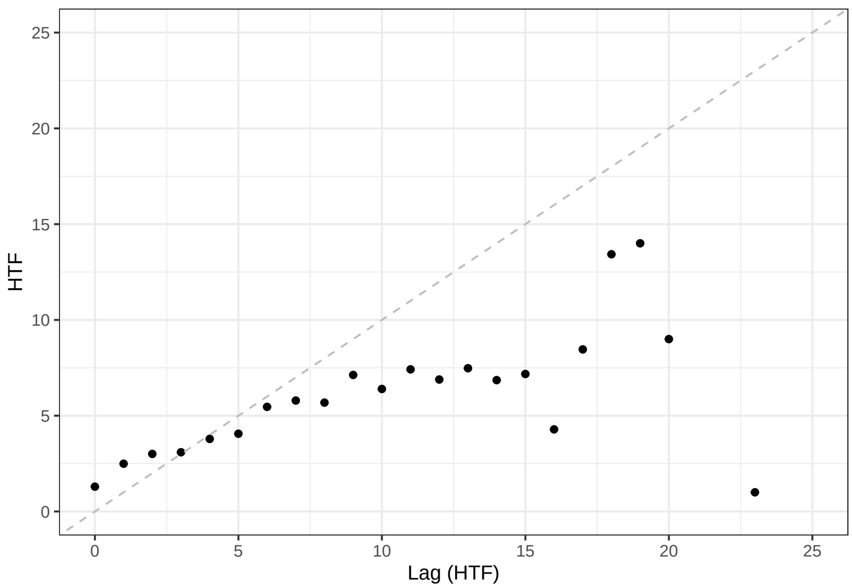
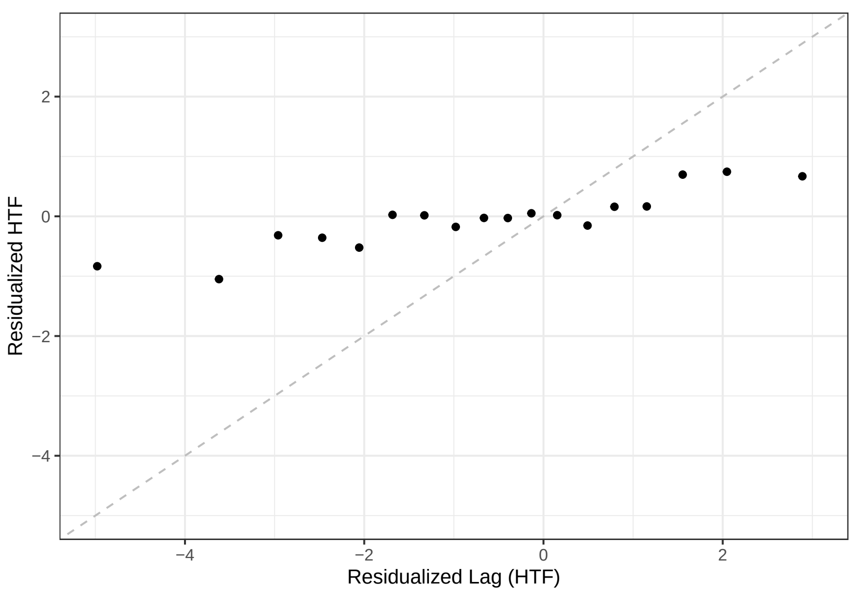


(a) Without FE



(b) With Year and Gauge FEs

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

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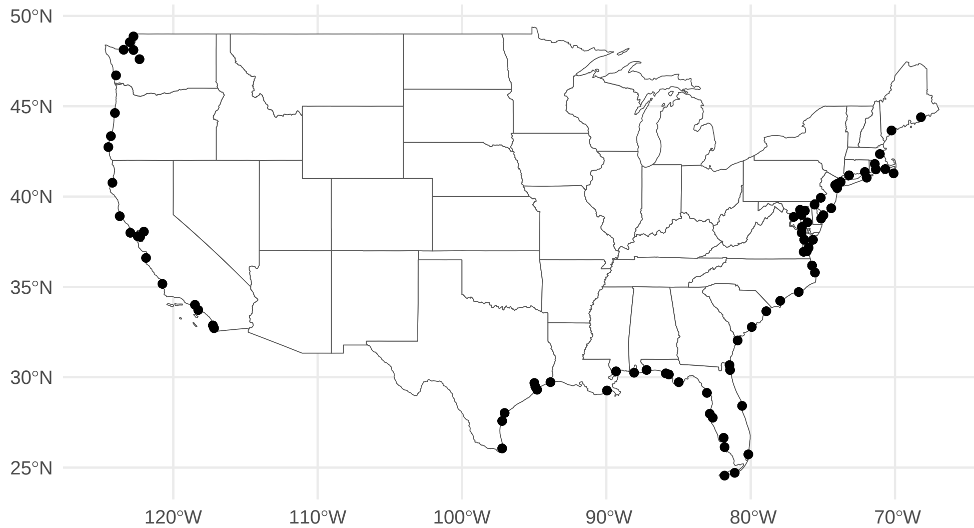

Figure A.3: Location of NOAA Gauge Stations. This figure depicts 84 NOAA gauge stations within the contiguous US that has flood thresholds from Sweet et al. (2018).

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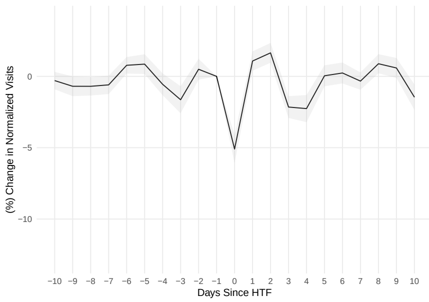
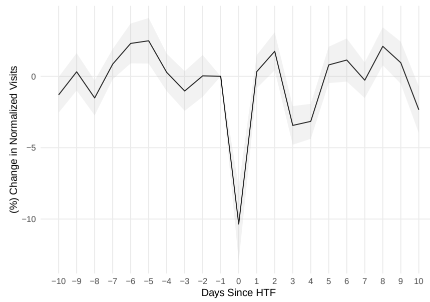
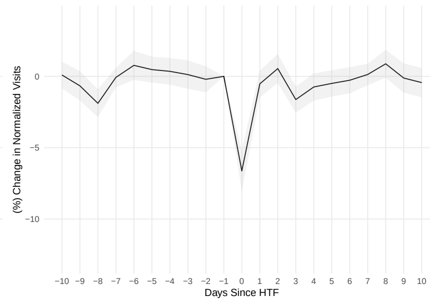


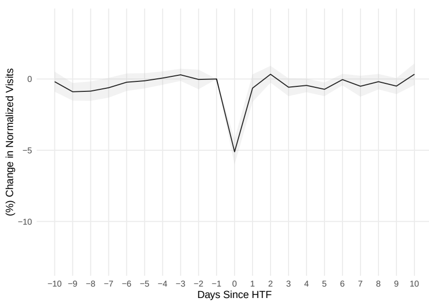
(a) Doctor Visits



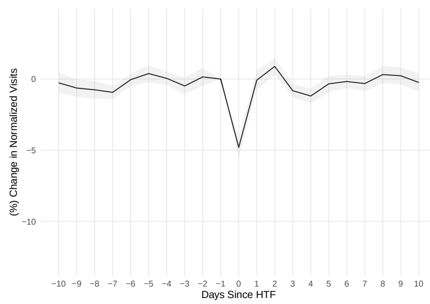
(b) School



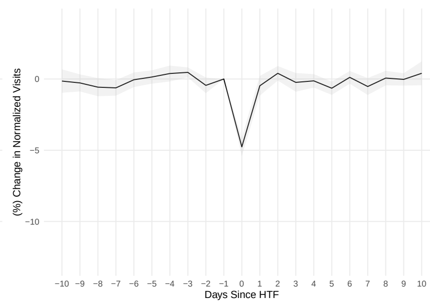
(c) Childcare



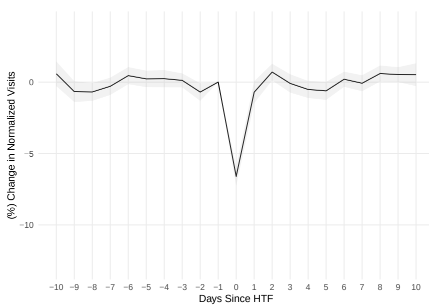
(d) Retail



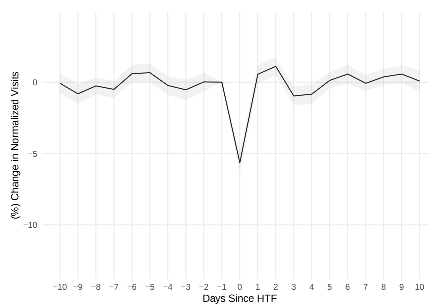
(e) Workplaces



(f) Restaurants



(g) Recreation



(h) Auto Repair

Figure A.4: The Effects of HTF on the Number of Daily Visits by Category. Panels (a)-(i) show the impact of HTF on the number of visits in 10 leads and lags for destination categories. We control for county by year, zip code by month, and date fixed effects. Grey areas show the 95% confidence interval.

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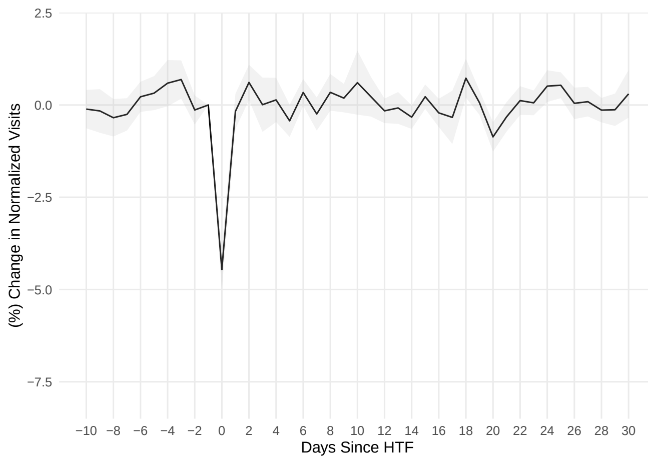
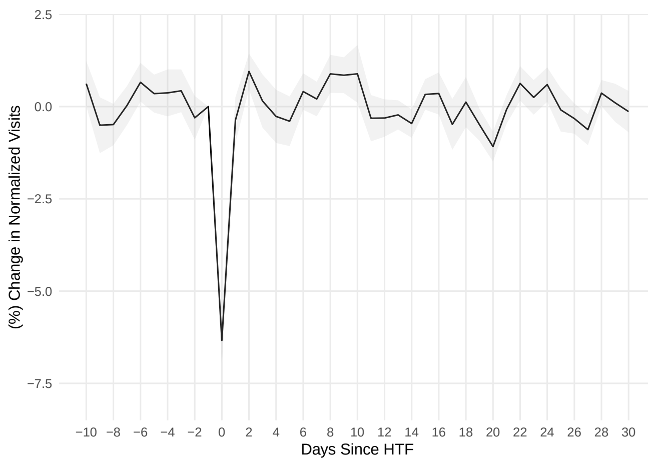


(a) Restaurant



(b) Recreation

Figure A.5: The Effects of HTF on the Number of Visits to Local Amenities. These plots show the HTF impact on the number of visits to local amenities in 10 leads and 30 lags. We control for county by year, zip code by month, and day-of-week fixed effects. Grey areas show the 95% confidence interval.

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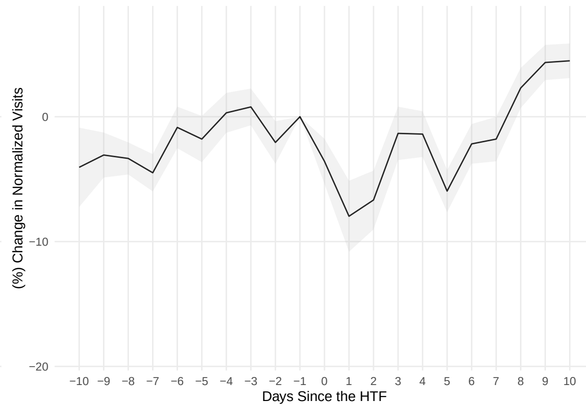
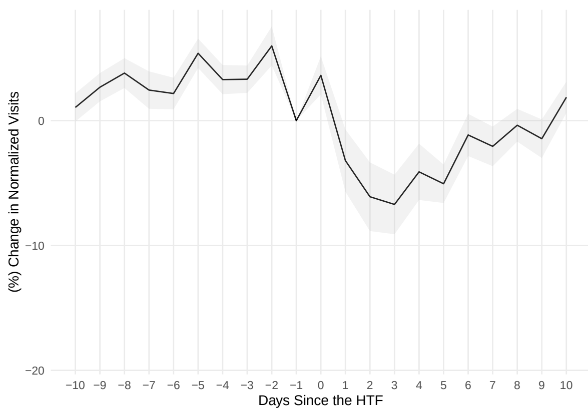
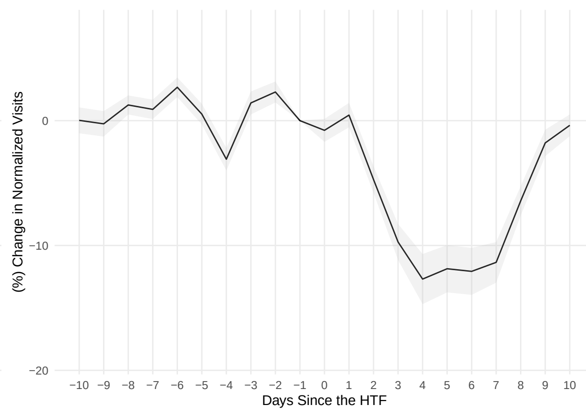
(a) 1- and 2-day PDD Flood



(b) 3- and 4-day PDD Flood



(c) 5- and 6-day PDD Flood



(d) 7+ day PDD Flood

Figure A.6: The Effect of PDD Floods on the Number of Daily Visits by Event Duration. These plots show the PDD impact on the number of visits during 10 days before and 10 days after a PDD event. We control for month by zip code, year by county, and day-of-the-week fixed effects, and daily precipication.

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