Beyond Asset Losses: Estimating the Economic Cost of Floods

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Abstract

While a theoretically consistent cost of floods is a welfare loss from the event, existing estimates are primarily based on asset losses due to measurement challenges. In this paper, we leverage variations in the occurrence of High-tide flooding (HTF), highly disruptive, yet rarely destructive small-scale coastal floods, to estimate the economic cost of floods. Our analysis reveals that on the day of HTF, the average number of visitors per point of interest reduces by 5%, suggesting significant disruptions in daily lives. Further, we show that exposure to one additional day of HTF in the past 12 months reduces rental rates by 0.25% or $51. Using this parameter, we show that a lower bound economic cost of Presidential Disaster Declaration floods is $4 billion per year, suggesting that asset losses alone may substantially underestimate the true cost of floods.

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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)

Economic theory suggests that the cost of floods is a utility loss from the event. This includes not only asset losses such as damaged properties but also myriads of economic costs beyond them—loss of income, loss of use value, negative health impacts, and the cost of compensatory actions. However, most existing cost estimates either capture asset losses alone or focus on specific dimension of economic costs (e.g., health impacts) because of measurement challenges (Gall et al. 2009, Smith and Katz 2013, Kousky 2014, Gallagher and Hartley 2017, Deryugina et al. 2018, Deryugina and Molitor 2020, Lee 2021).[1] This practice, which may lead to a substantial underestimation of the true cost of floods, is not merely a theoretical concern. Rather, it bears an enormous practical importance because an accurate estimate of the cost of floods is a prerequisite for investing in socially optimal level of flood, and more broadly, climate change mitigation efforts (National Research Council 1999).[2]

This paper aims to fill this gap in the literature by providing the first estimate of the economic cost of floods beyond asset losses. For this, we leverage variations in the frequency of High-tide flooding (HTF), highly disruptive, yet rarely destructive small scale coastal floods, and causally identify the impact of HTF on rental rates. Building on the hedonic approach, we interpret this parameter as the willingness-to-pay (WTP) for avoiding disruptions due to HTF, or a lower bound economic cost of floods. Additionally, we investigate HTF's impact on mobility to provide concrete evidence of its disruptive effects.

HTF refers to the temporary inundation of low-lying coastal areas during exceptionally high tide events, distinguishable from typical floods by its occurrence even on clear, sunny days (Sweet 2018).

[1] A large body of literature estimate the cost of natural disasters using macroeconomic outcomes. (Nordhaus 2010, Strobl 2011, Cavallo et al. 2013, Hsiang and Jina 2014, Desmet et al. 2021). However, GDP is a poor measure of welfare (Fleurbaey 2009). Further, macroeconomic outcomes have little guides for cost-benefit analysis of flood prevention measures and can provide limited insights on mechanisms.

[2] Recent studies highlight the linkage between climate change and more intense and frequent natural disasters (Bilal and Känzig 2024). Thus, a higher economic cost of floods will support a more aggressive greenhouse gas reduction measures.

This phenomenon is driven by a combination of weather conditions, such as wind speed, oceanic factors like water density and currents, and tidal forces (Sweet 2018). The variability of these conditions create significant fluctuations in the frequency of HTF occurrence over time and space. Moreover, the intricate physics underlying HTF makes its prediction extremely challenging for layperson especially given lack of forecast products, providing us with a plausibly exogenous variation for our empirical analysis (Dusek et al. 2022).

To leverage these variations, we collect daily water level records from 84 NOAA gauge 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 zip code level daily number of visits per point of interest (POI) data from Safegraph (2018-2021). To determine the area inundated by the HTF (i.e., spatial extent of the HTF), we use the HTF inundation map from NOAA.

We start our empirical analysis by testing the "first-stage" effect, namely whether HTF disrupts daily lives or not. Building on the earlier findings that HTF negatively affects road conditions (Jacobs et al. 2018, Hino et al. 2019, Hauer et al. 2021, Hauer et al. 2023), we focus on the impact of HTF on mobility. Specifically, we use the distributed lag model around the HTF occurrence and find that on the day of HTF, the average number of visitors per POI drops by 5% in inundated zip codes. While non-trivial in magnitude, this estimate should be a lower bound impact because it does not capture the intensive margin effect in travel time. We also find no anticipation effects, consistent with the limited of predictability. Remarkably, zip codes within 100 km of the coastline that are not directly inundated still experience a 3.6% reduction in the number of trips, which suggests a substantial spatial spillover effect. Given the essential role of mobility in accessing work, food, education, hospitals, and leisure, these results imply significant utility losses due to HTF.

Turning to the effects of HTF on rental rates, we first posit that tenants form expectations about the likelihood of HTF during the rental period by recent experiences following the literature (Kahneman 2011, Bin and Landry 2013, Gallagher 2014). Then, by exploiting year-to-year variations in HTF frequency, we estimate how the number of days in the past 12 months affects rental rates. We find that having one additional day of HTF, which proxies for an increase in the expected number of days with HTF during rental period, reduces the average rent by 0.25% or \$51 at the mean annual rental rate for zip codes inundated by HTF. Building on the hedonic model, we interpret \$51 as

MWTP to avoid one additional day of HTF, or one additional day's worth of lower bound economic cost from floods. Further, consistent with mobility impact results, we find that coastal zip codes not inundated by HTF still experience a 0.13% reduction in rental rates, suggesting that impaired mobility is one of the key mechanisms behind rental price adjustments. Additionally, consistent with our assumption on belief formation, we find that the farther past and future HTF exposures do not impact current rental rates.

Using the estimated parameter, we calculate an economic cost of large floods, using the Presidential Disaster Declaration (PDD) floods as examples. For this, we take $51 and multiply it by the number of households living in a zip code exposed to the PDD floods and by each events' duration. The resulting economic cost is as large as $4 billion per year over the 2018–2021 period. Although this figure is already substantial, we believe this number is likely to be a lower bound because (1) economic costs of large floods are much larger 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 three different strands of literature. First, it complements earlier studies estimating the cost of natural disasters. These papers typically rely on either damage on physical assets (Smith and Katz 2013, Lee 2021, Wing et al. 2022) or specific dimensions such as long-term health or labor market impacts (Deryugina et al. 2018, Deryugina and Molitor 2020) or financial distress (Gallagher and Hartley 2017) to measure the cost of natural disasters. This paper provides the first cost estimate that captures a wide range of the economic costs beyond asset losses by linking a novel identification strategy to the hedonic framework. The findings indicate that ignoring economic costs can substantially underestimate the true cost of floods. Further, given that wildfire or earthquake also prompts various defensive behaviors and/or income losses (National Research Council 1999, Jones et al. 2016), the estimate of this paper can shed light on economic costs from other types of natural disasters as well.

Second, despite scientific findings that HTF will evolve from an occasional nuisance to a regular problem (50+ days with HTF per year) for many coastal cities as early as 2030 (Thompson et al. 2021), our understanding on the impact of HTF is very limited because voluminous 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 studying the impact of HTFs (Jacobs et al. 2018, Hino et al. 2019, Hauer et al. 2021, Hauer et al. 2023, Mueller et al. 2024) by providing the first national scale empirical evidence on the mobility and rental market impact.

Finally and more broadly, this paper builds on the literature on avoidance behavior in response to environmental disamenities such as air pollution (Neidell 2009, Deschênes et al. 2017, Ito and Zhang 2020), drinking water quality (Zivin et al. 2011, Hadachek 2022), or hurricanes (Beatty et al. 2019). We extend these studies by presenting evidence of a novel form of defensive behavior in response to flood risks.

This paper proceeds as follows. Section 2 lays out a framework that conceptualizes the economic cost and guide 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 estimate the economic cost of PDD floods. Section 7 concludes.

2 Conceptual Framework

We introduce a simple conceptual framework based on the hedonic model that examines the tradeoff between housing prices and risks (Gayer et al. 2000, Davis 2004, Viscusi and Gayer 2005, Bosker et al. 2019). Consumers 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 lives, $U_D > U_F$ for all values of (z, x). For instance, consider the proximity to work (i.e., commuting distance), an important component of z. The proximity will have much smaller value when access to workplace is restricted due to flooded roads. Similarly, the utility derived from tasty food (an example of x) diminishes considerably when gatherings with friends cannot occur due to floods.

The consumer rents one house at rental rate r, which is a function of z and p the probability of flood during rental period. Then, each consumer's bid function consists of (r, p) pairs that satisfy equation (1).

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

In a competitive market, the hedonic price schedule is determined by the equilibrium interactions of buyers and sellers. The first order condition in equation (2) implies that the gradient of the hedonic price schedule with respect to flood risk ($\frac{\partial r}{\partial p}$) is equal to the monetized utility difference between the two states D and F or MWTP to avoid utility reduction due to floods, which we refer to as the "economic cost" of floods.[3] Importantly, equation (2) implies that the economic cost can be empirically estimated by regressing flood belief on rental rates.

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

Take theory to data. Equation (2) provides guidance for our empirical exercise. First, we empirically test if $U_D > U_F$ by estimating the impact of HTF on mobility. Given that HTF's primary impact is on impairing road conditions, which critically determines access to various POIs people value, adverse impact of HTF on the number of trips can be an informative proxy for utility shocks from the event.

Second, equation (2) suggests that we need data on the belief on the probability of floods during rent period (i.e., belief about future). However, what we can observe is the past HTF exposure. Following the literature, we posit that people form their expectation on future likelihood of HTF based on the recent experience (Kahneman 2011, Bin and Landry 2013, Gallagher 2014). Such belief formation is consistent with availability bias or Bayesian learning model with imperfect information. Further, because our focus is on estimating the impact of HTF on the short-term flow of utilities from a housing service—rather than its impact on long-term housing price expectations—we use rental rates for our empirical exercises. Indeed, Bishop et al. (2020) points out that rental rates may better reflect current amenity flows than housing prices although renters may have weaker incentive to become fully informed about local amenities. In Section 5, we show that high tide seems to be as salient as flash floods and a typical renter stays long enough to accumulate local knowledge.

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

Finally, equation (1) helps to highlight why the HTF based economic costs estimates will underestimate the economic costs from larger floods. For this, it is helpful to divide vector of z into two segments: z_1, which represent structural attributes of a property, such as the number of bedrooms or the building's physical condition and z_2 that captures amenities like proximity to work. Now, as detailed in Section 3.1 and 5, HTF typically inflicts minimal direct damage, rarely causing changes in z_1. In contrast, larger flood events such as hurricanes will negatively impact z_1 (e.g., roof is damaged), 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

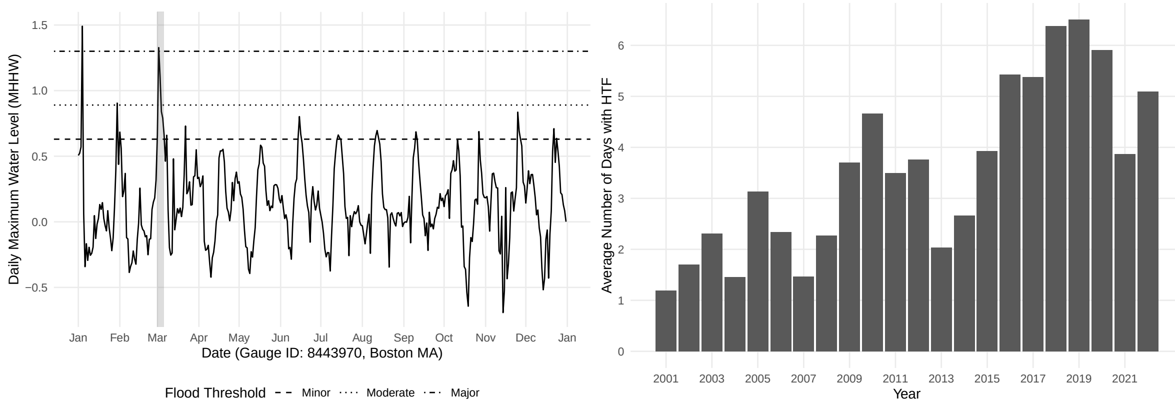
3.1 High-Tide Flooding

Measurement. To illustrate how we measure HTF (in time), in Figure 3.1 (a), we overlay daily water height time series with flood thresholds from a gauge station in Boston. Following the definition of HTF from NOAA, we create an indicator variable that takes 1 when daily maximum water level is between the minor and moderate gauge specific-flood thresholds (for instance, Jun 15 in the figure). Importantly, the highlighted grey area (March 4, 2018) suggests that water levels can exceed the minor threshold as a precursor to or a descendant of a larger flood event. In defining HTF, we exclude these cases to limit the impact of large direct damage incurred by 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 in our regression models.

To measure HTF in space—namely, identifying the areas inundated by HTF—we use NOAA inundation map.[4] The map delineates the boundary of inundation area upon the HTF occurrence using the "bathtub approach", which compares the predicted water surface level to the land elevation (NOAA 2017).

Trend and impact. 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 contigu-

[4] Accessed at https://coast.noaa.gov/slrdata/. We use the "Flood Frequency" product.



(a) HTF Measurement

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

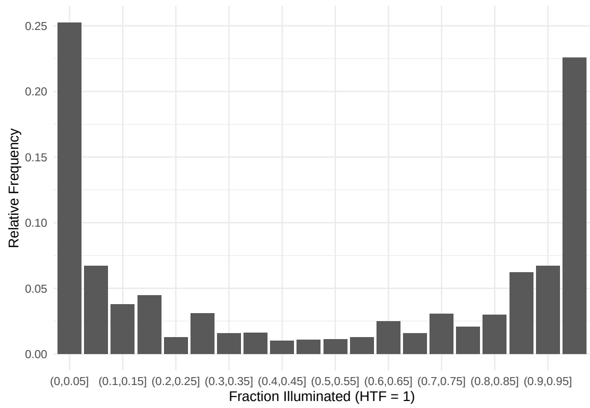
Figure 3.1: High Tide Flooding Measurement and its Trend Over Time. Panel (a) shows high tide flooding measurement at the gauge level. Panel (b) illustrates the number of days with HTF between 2001 and 2022 averaged over the 84 NOAA gauge stations located within the contiguous US.

ous US has more than tripled in the past two decades (Figure 3.1 (b)). Further, 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).

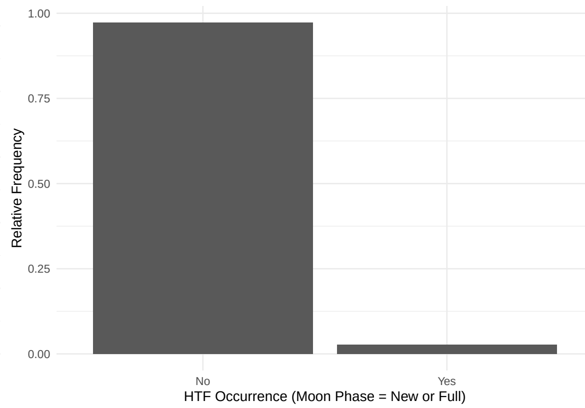
Existing anecdotal and scientific evidence suggests that HTF seriously disrupts daily lives. For instance, people experience loss of income (e.g., less patron visits to restaurants), loss of use value (e.g., giving up outdoor exercise at a park), health risks (e.g., delayed ambulance services) or other nuisances (e.g., wading through brackish water and suffering skin rashes) (Flechas and Staletovich 2015, Alvarez and Robles 2016, Kensinger 2017, Hino et al. 2019, Mazzei 2019, Hauer et al. 2021, Bittle 2022, Hauer et al. 2023).

Despite these disruptions, asset losses from HTF are low. In Appendix Figure B.1, we plot the dollar amount of the National Flood Insurance Program (NFIP) claims by flood types. Panel (a) shows that over 80% of HTF events have no claims at all. This is in a stark contrast to Panel (b) where more than 50% of events incur non-zero claims and 75% of claims value (conditional on positive claims) are over $90,000. Indeed, the mean claims value at the community level for larger floods are over 45 times larger than HTFs ($42,900 vs. $19,718,000). In Section 5, we provide more rigorous investigation on the impact of HTF on asset losses.

HTF as a research design. A critical assumption in our empirical strategy is that HTF occurrence—both in terms of precise timing (for Section 4) and the year-to-year variation in



(a) Fraction Illuminated (HTF = 1)



(b) HTF Occurrence (Moon Phase = New or Full)

Figure 3.2: HTF as a Research Design. These figures show (a) the distribution of moon illumination conditional on the HTF occurrence and (b) the probability of HTF occurrence conditional on new or full moon phase.

HTF frequency (for Section 5)—is plausibly random, or in other words, unpredictable. However, daily water level time series in Figure 3.1 (a) suggests that the water level closely follows moon phase, which may allow people to anticipate disruptions in advance and adjust their behavior accordingly.

Indeed, Figure 3.2 (a) shows that conditional on a day with HTF occurrence, it is more likely to be either full moon or new moon phase (i.e., moon illumination below 5% or over 95%). However, the figure also implies over roughly 50% of HTF happens outside of the full or new moon phase. Figure 3.2 (b) further shows that conditional on new or full moon phase, less than 3% of days have a HTF, which suggests that moon phase has limited value for HTF prediction.[5]

To investigate predictability of year-to-year variations in HTF frequency, in Appendix Figure B.2, we plot the annual number of days with HTF for gauge stations located in selected states (Maryland, South Carolina, and Virginia). These figures show that for a given location, there is substantial year-to-year variation in the number of days with HTF, which makes it difficult to predict the number of future events based on past occurrences. Further, cross-sectional variation is also large despite relative proximity of these gauge stations.

[5] An average zip code in the sample has 5.92 HTFs in a given year over the 2018–2021 period. From Figure 3.2 (a), we know that roughly 3 HTFs would happen on new or full moon phase. Given that the number of days in the new or full moon phase (i.e., moon illumination below 5% or over 95%) are 103 per year, smaller than 3% seems plausible. Also, it is worth pointing that similar conclusion holds even if we restrict our sample based on season and location where tidal forcing is a stronger predictor. Specifically, the fraction of days with HTF goes up to 5% when we focus on fall and winter in Maine, Oregon, Washington, and San Diego based on Sweet (2018).

Such a lack of predictability is consistent with complex physics behind the HTF, which is determined by three factors: weather conditions, such as wind speed, oceanic factors like water density and current patterns, and tidal forces (Sweet 2018). Further, lack of forecast products during our study period makes anticipatory behavior even harder. While the National Weather Service has been releasing coastal flood advisory, it is typically announced near the actual event. NOAA released its first monthly outlook product only in August 2023 (NOAA 2023). Combining these factors together, HTF exposure over time and space provides a plausibly exogenous variation for our empirical analysis (Dusek et al. 2022).

3.2 Data Description

Water levels. We construct coastal flood history data using the NOAA water levels data from 84 gauge stations in the contiguous US (See Appendix Figure B.3 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 gauge-specific flood thresholds from Sweet (2018), which is objective and nationally consistent set of minor, moderate, and major coastal flooding thresholds, to detect flood events.

Mobility. To explore the HTF's impact on mobility, we use mobile phone based visit counts data from SafeGraph. The data documents daily number of visits to 12 million points of interest (POIs) in the US from 45 million smartphone users for 2018–2021.[7] The data also provide the location information for each POI at the census block group level and its industry category based on the North American Industry Classification System (NAICS) code. For empirical analysis, we first assign each POI to a zip code by spatially matching census block group to zip code and aggregate POI level data to the zip code level. While Safegraph data allow for analyzing mobility patterns with high spatial and temporal granularity, previous studies have documented measurement issues (Parolin and Lee 2021, Kurmann and Lalé 2022, Knittel et al. 2023). In Appendix A, we discuss these potential concerns in detail and describe how we address them.

Rental rates. Rental rates information comes from the Zillow Observed Rent Index (ZORI). The

[6] For datum, we use mean higher high water (MHHW) following NOAA flood thresholds.
[7] See https://docs.safegraph.com/docs for more details (accessed on Jun 15, 2023).

index is constructed by taking weighted average of asking prices within the 35th to 65th percentile price range on properties repeatedly listed for rent on Zillow.[8] The index is dollar-denominated and we adjust for inflation using CPI. 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. Given that HTF is unlikely to have any impact for inland states, we restrict our sample to the zip codes within the 22 states in the contiguous US that appear in the NOAA inundation map.[9] 1,471 zip codes that have both rental information and an overlap with the NOAA inundation map form the main analysis sample.

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)).

NFIP claims. We use “OpenFEMA Dataset: FIMA NFIP Redacted Claims – v2” from FEMA to investigate the impact of HTF on asset losses.[10] The data have over 2 million individual property level claims information such as claims dollar amount and zip code from 1978 to 2024. We aggregate the data to the zip code by month level and merge it to the rental rates data.

3.3 Summary Statistics

In Figure 3.3 (a), we show the distribution of the number of days with HTF in the past 12 months from our main sample. The histogram shows that more than 80% of zip code–month had experienced at least one HTF in the past 12 months. Also, the shape of the distribution suggests that the average number of days with HTF (5.6) is unlikely to be driven by a few extreme values.

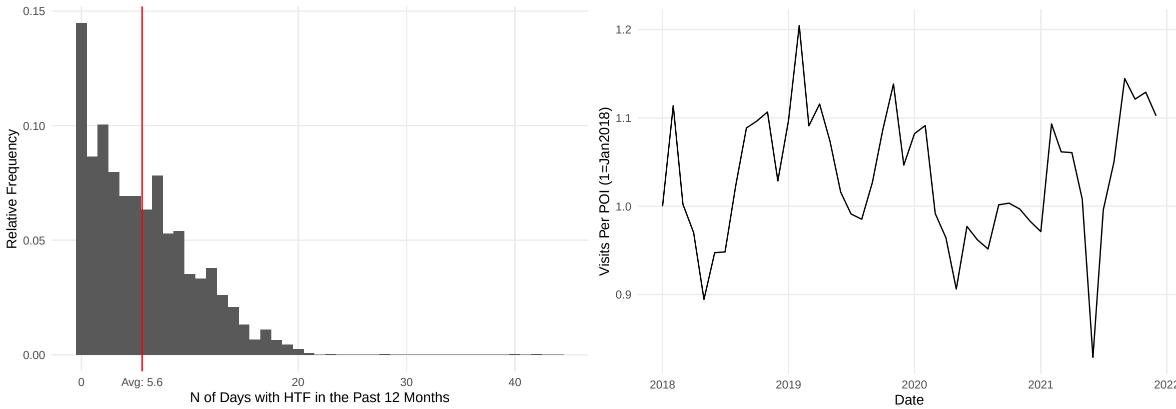
In Figure 3.3 (b), we present the average normalized visit counts per POI over the 2018–2021 period.[11] To account for time varying sampling rates—namely, the number of cellphone devices included in the Safegraph data, we divide the raw visit counts by the number of cellphone devices (see

[8] Weights are used to match with the characteristics of housing stock documented in Census data. For more detail, see https://www.zillow.com/research/methodology-zori-repeat-rent-27092/ (accessed on Mar 2, 2023).

[9] 22 states are AL, CA, CT, DE, FL, GA, LA, MA, MD, ME, MS, NC, NH, NJ, NY, OR, PA, RI, SC, TX, VA, and WA.

[10] Downloaded from https://www.fema.gov/openfema-data-page/fima-nfip-redacted-claims-v2.

[11] Safegraph data started in 2018.



(a) Number of Days with HTF (Past 12 Months) (b) Average Number of Visits Per POI (base = 2018)

Figure 3.3: Summary Figures. These figures show (a) the histogram of the number of days with HTF events at the zip code level and (b) the average number of visits per POI over time.

Appendix A for more details). As Appendix Table B.1 shows, the vast majority of POIs in the data are non-work related POIs such as retail stores, restaurants, entertainment and health care. These POIs are everyday destinations with frequent visits, which is useful to detect any anomaly in the number of visits caused by HTF. Indeed, the time series suggests that for most of the time, the number of visits are stable within ± 10% from the base in January 2018.

Table 3.1 shows summary statistics for other key variables used in our empirical exercise. A few points are worth noting. First, an average annual rent for the zip codes that has any overlap with the NOAA inundation map—which is our primary sample—is $20,419. This is nearly $4,000 higher than the average annual rent for all other zip codes in the Zillow rent dataset that are not overlapping with the inundation map.[12] The difference in the rental rates (at least partly) reflects amenity value of being closer to the ocean. In addition to a large spillover effects reported in Section 4, 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 leverages variations across inundation areas.

Second, the minimum value is the distance from a zip code centroid to the closest coastal line is on average 5.6 miles but a large standard deviation suggests that non-trivial number of zip codes are over 40–50 miles away from the coastal line. While this seem implausible given that the event is driven by tidal movement, this can happen through interconnected rivers leading on the the ocean.

Third, the number of days with HTF in the past 12 months is an order of magnitude higher

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

Table 3.1: Summary Statistics for Key Variables

Variables	Min.	Max.	Mean	Std.Dev.	N
Annual Rental Rates	150	391,867	20,419	12,288	119,507
Distance to the Coast (Miles)	0.02	102	5.7	9.9	119,507
N High Tide Floods (in Past 12 Months)	0	44	5.6	4.9	119,507
N Larger Floods (in Past 12 Months)	0	11	0.48	0.99	119,507
N NFIP Claims	0	3,986	0.79	21.9	119,507
$ Value of NFIP Claims	0	409,665,404	43,251	1,942,917	119,507

than that of larger floods. An average community experience 0.8 flood insurance claims worth over $40,000 for an average month. However, as a large standard deviation suggests, these are driven by extreme values.

4 High Tide Flooding and Impaired Mobility

Estimation framework. In this section, we test if $U_D(z,x) > U_F(z,x)$ by investigating the adverse impact of HTF on mobility. For this, we estimate a distributed lag model as equation (3).

$$Visits_{zdt} = \sum_{j \in [-10,10], j \neq -1} \beta_j F_{zt,d-j} + \gamma \mathbf{X}_{zdt} + \alpha_{zm} + \lambda_w + \theta_{ct} + \epsilon_{zdt} \tag{3}$$

Here $Visits_{zdt}$ is the average number of visits per POI for zip code z in date-year dt (e.g., Jan 1, 2019). To account for potential measurement errors inherent in cellphone based mobility data, we normalize the number of visits by the zip code specific number of cellphone devices following Kurmann and Lalé (2022) (for more details, see Appendix A). $F_{zt,d-j}$ are 10 leads and lags of HTF occurrence in zdt. We control for zip code-level weather events X_{zdt}, which include moderate or larger flood event occurrence and daily precipitation. 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 county specific macro level shocks that might affect visits, such as the differential impact of pandemic across counties. Finally, λ_w is included to account for differences in visit patterns by day of the week (e.g., Monday, Tuesday, etc). The coefficient of interest is β_j, the effect of HTF on the number of visits per POI for $j \in \{-10, 10\}$ relative to $j = -1$. 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.

While equation (3) informs the impact of HTF averaged over all zip codes in the sample, it is also useful to estimate zip code specific mobility effect. This provides us additional approach to examine potential spillover effects. For this, we estimate a more parsimonious equation (4), where $F_{zdt} = 1$ if there is HTF for z on date-year dt. We cluster standard errors at the fortnightly level to account for potential serial correlation in the error.

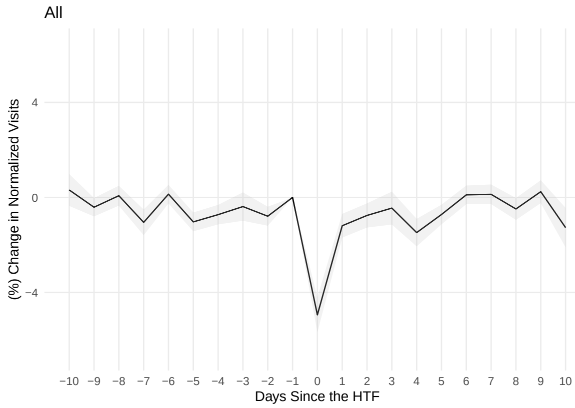
$$Visits_{zdt} = \beta_z F_{zdt} + \gamma \mathbf{X}_{zdt} + \alpha_m + \lambda_w + \theta_t + \epsilon_{zdt} \tag{4}$$

Results. Figure 4.1 illustrates the impact of HTF on the number of visits per POI. Panel (a) shows that on the day of HTF, the number of visits per POI decreases by 5% compared to the previous day, indicating that HTF seriously disrupts mobility.[13] It is important to note that a 5% reduction only captures the extensive margin effect, and thus underestimate the extent of disruptions. That is, while some individuals might still complete trips by taking alternative routes or driving more slowly—thereby incurring additional time costs—these adjustments are not reflected in the estimate in column (1).[14]

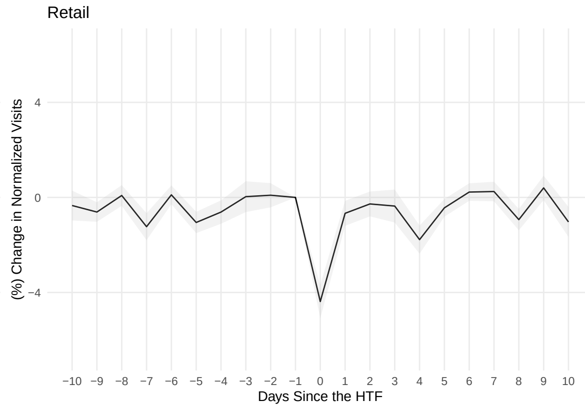
Panel (a) also allows us to evaluate the dynamic effect. We observe no anticipatory behavior; specifically, the number of visits one or two days before HTF does not exceed other days, indicating that individuals do not make preemptive trips. This pattern starkly contrasts with responses to extreme temperatures or natural disasters, where households typically increase store visits in advance to fulfill their needs while avoiding travel on the day of the event (Beatty et al. 2019, Lee and Zheng 2023a). This difference can likely be attributed to predictability issues: while forecasts for natural disasters and extreme temperatures are widely available, similar predictive services do not exist for HTF. Furthermore, the absence of a rebound effect post-HTF suggests that the flooding reduces rather than merely postpones activities.

[13] Equation (3) is estimated in levels, and the estimated coefficient is divided by the mean of the dependent variable to express the effect in percentage terms. The results in their original scale and the means of the dependent variables are presented in Appendix Table B.2. For readability, dependent variables are multiplied by 1,000.

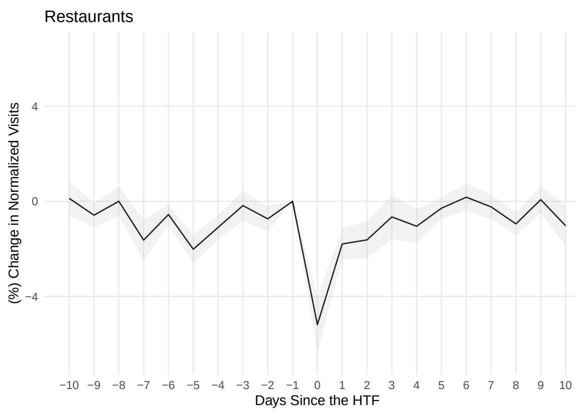
[14] There is limited data on the increased time effect due to HTF but a back-of-the-envelope calculation suggests that each HTF is likely to cause non-trivial increase in travel time. For instance, take the annual HTF induced additional driving time (2 hours) per vehicle from Jacobs et al. (2018) and 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).



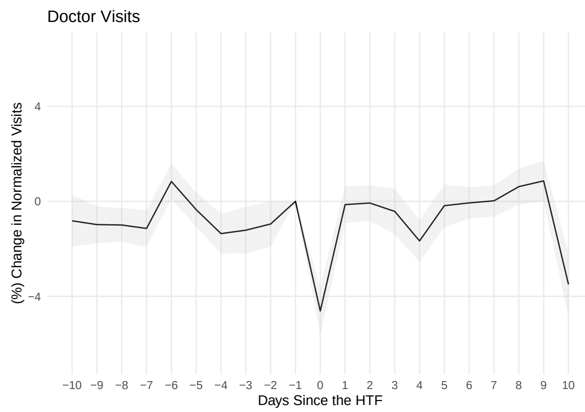
(a) All POIs



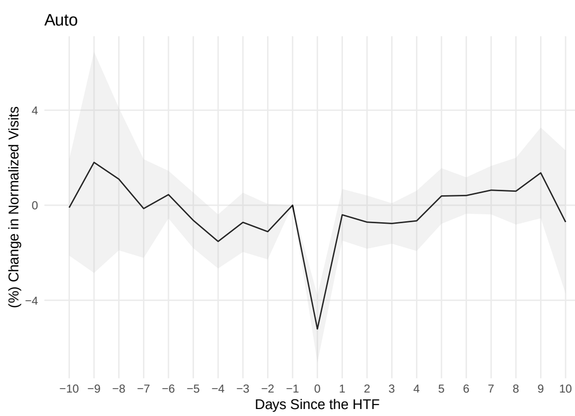
(b) Retail



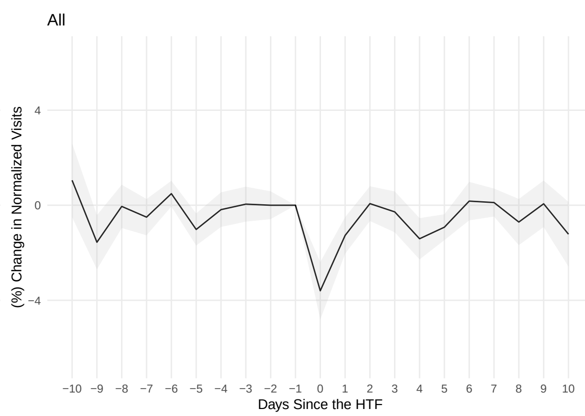
(c) Restaurant



(d) Doctor Visits



(e) Auto Repair



(f) All - Spillover

Figure 4.1: The Effects of HTF on the Average Number of Daily Visits by Time. These plots show the HTF impact on the number of visits in 10 leads and lags. We control for moderate or larger flood event occurrence, precipitation, county by year fixed effects, zip code by month fixed effects, and day-of-week fixed effects. Grey areas show the 95% confidence interval.

Before turning attention to industry specific effects in Panels (b)-(e), it is worth highlighting the impact of larger floods on the number of visits. In Appendix Table B.2 column (1), we report coefficients that correspond to Panel (a) including coefficients for a moderate and major floods. We find that the impact of floods on mobility is monotonically increasing in flood size: a moderate (major) flood event reduces the number of visits per POI by 2.5 and 3.5 times larger than a HTF. This is plausible given that (1) more POIs and roads are likely to be closed during larger floods, and (2) driving during larger floods typically involves higher risks.

In Figure 4.1 (b) and (c), we analyze the impact of HTF on the retail and restaurant sectors, which are collectively accounting for over 40% of all visits (see Appendix Table B.1). We find that the effects on these two sectors are largely similar, though the impact on restaurants appears slightly greater. This observation aligns with the unpredictability of HTF; since retail products can generally be stored more easily than restaurant offerings, one would expect a more pronounced impact on retail if anticipatory behaviors were significant.

Panel (d) shows the impact of HTF on doctor visits. Similar to other destination categories, we find a sharp reduction in the number of trips on the day of HTF. This suggests that HTF can have health implications and the economic cost of HTF can be much larger than a small nuisance. Indeed, Mueller et al. (2024) finds that HTF increases mortality risk among elderly individuals by causing delays in emergency medical care due to unfavorable road conditions.

In Panel (e), we leverage the impact of HTF on auto repair shop visits to examine potential impact of HTF on physical assets. In comparison to other categories, there seems to be a small rebound effect after 5–9 days from the event. However, the cumulative effect of HTF on the number of visits in the post period ($\sum_{j=0}^{10} \beta_j$) is still 5.1% lower than the baseline. Finding in Panel (e) is consistent with Figure B.1 that HTF rarely incurs large asset losses.

Finally, in Panel (f), we investigate potential spillover effects. For this, we estimate equation (3) on zip codes that are not overlapping with the NOAA inundation map but are located within 100km from the coastal line and are included in the Zillow dataset. The estimated coefficients in Panel (f) indicate that the number of trips reduce by 3.6% on the day of HTF in comparison to the previous day. This indicates that unless the NOAA inundation map is seriously underestimating the true extent of HTF, zip codes that are not directly inundated by HTF also suffer the inconvenience, although the magnitude seems to be smaller. This spillover effect is plausible, as trips are likely to be discouraged if either the origin or the destination is inundated, or if a critical road segment connecting the two is affected by flooding. Consistent with this, Hauer et al. (2021) finds that the areas affected by HTF-induced traffic disruption can be much larger than the inundated areas.

The zip code-specific HTF impact, estimated using Equation (4), provides a detailed perspective on the spillover effects. In Figure 4.2, darker zip codes are those that are overlapping with the NOAA inundation map and have negative zip code specific mobility effect for (a) Florida and (b) California. Consistent with Panel (f), a substantial number of zip codes, depicted in light grey, also exhibit a negative mobility effect despite not overlapping with the inundation map. Appendix Figure B.4 (a) illustrates that similar pattern emerges across all coastal zip codes in the contiguous US. Further, Panel (b) confirms that this conclusion holds even when focusing solely on zip codes with statistically significant impacts at the 90% confidence level.

5 Effect of High Tide Flooding on Rental Rates

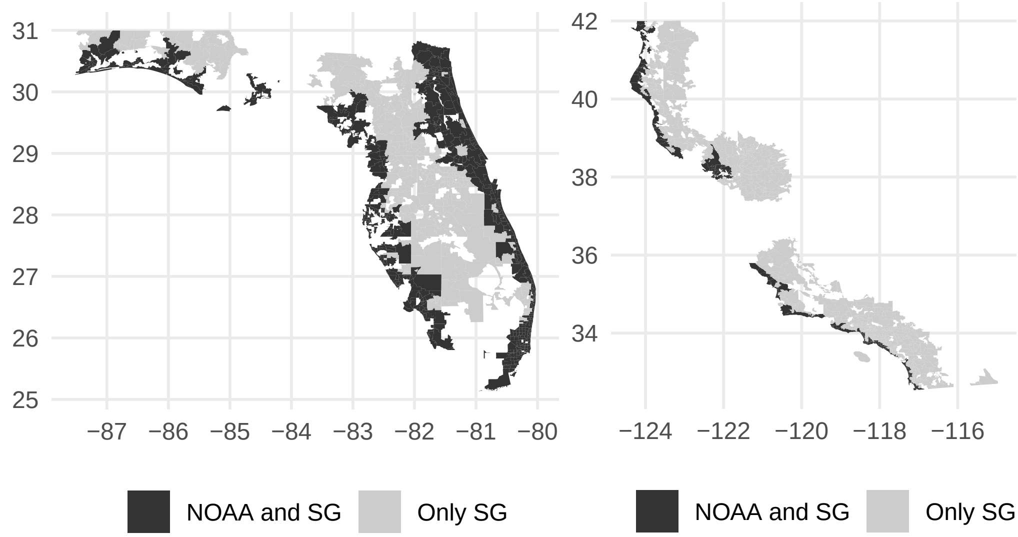
Estimation framework. Results in Section 4 provides the "first-stage" evidence that HTF substantially disrupts daily lives, namely $U_D > U_F$. This section aims to quantify $U_D - U_F$ and estimate the economic cost of floods by estimating the impact of HTF on rental rates using equation (5).

$$log(Y_{czmt}) = \beta N_{zmt} + \gamma \mathbf{X}_{zmt} + \alpha_z + \theta_{ct} + \theta_m + \epsilon_{czmt} \tag{5}$$

Here Y_{czmt} is the 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 meant to control for the impact of larger floods and weather conditions—the number of days with moderate or major flood events in the past 12 months, and monthly precipitation—and demand shifters—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 exclusion of 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 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. As discussed in Section 2, following the literature, we assume that people



(a) Florida (b) California

Figure 4.2: Inundated vs. Affected Zip Codes. These maps depict coastal zip codes in Florida and California. Darker color indicates zip codes that are overlapping with the NOAA inundation map and experience negative mobility impact from HTF while lighter color indicates zip codes that experience negative mobility impact even though they are not overlapping with the NOAA inundation map. For this, we estimate zip code specific impact of HTF for all zip codes within 100km from the coastal line using equation (4).

form expectation about the likelihood of HTF during rental period based on recent past (Kahneman 2011, Bin and Landry 2013, Gallagher 2014).[15] This means that N_{zmt} proxies for p in equation (2), which allows us to interpret β as the MWTP for avoiding HTF exposure. Further, because of the non-destructive nature of HTF, β can be interpreted as a lower bound economic cost of floods per day. We show that the estimated effect is robust to alternative specifications including a non-parametric approach where we use a set of HTF frequency bins as key regressors.

It is important to note that our main sample consists of zip codes that are overlapping with the NOAA inundation map, which means that we identify the impact of HTF by exploiting year-to-year variations in HTF frequency for zip codes that are directly exposed (i.e., inundated) upon the HTF occurrence. A natural alternative would be using zip codes that are not intersecting with the inundation map but are adjacent to the exposed zip codes as a control group. We do not pursue this approach because of a large spillover effects documented in Figure 4.1 (f).

Results. Table 5.1 column (1) reports that being exposed to one additional day of HTF within the

[15] We choose 12 months because 12-month leases are most common (60%) in the US (see https://www.bls.gov/spotlight/2022/housing-leases-in-the-u-s-rental-market/home.htm accessed on Mar 19, 2024).

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

	(1)	(2)	(3)	(4)
Dependent Var.:	log(Rent)	log(Rent)	Claim Ct	Claim Ct
N Days with HTF (Past 12 Months)	-0.0025***	-0.0013***		
	(0.0004)	(0.0005)		
N of Days with Larger Floods (Past 12 Months)	0.0012	0.0013		
	(0.0016)	(0.0013)		
N Days with HTF (Past 2 Months)			-0.1455	-0.4397
			(0.1380)	(0.3341)
N of Days with Larger Floods (Past 2 Months)			4.582***	5.880*
			(1.509)	(3.481)
Sample	Inundated	No Inund	Inundated	No Inund
Fixed-Effects:				
Zip Code	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Year by County	Yes	Yes	Yes	Yes
Observations	119,493	146,616	119,493	146,980

Note:
This table presents the impact of recent HTF exposure on rental rates (columns (1) and (2)) and flood insurance claims (columns (3) and (4)). Baseline controls (number of days with moderate or major flood events, monthly precipitation, 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. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

past 12 months reduces average rent by 0.25%, which amounts to a \$51 reduction in the annual rent (evaluated at the mean annual rent per unit \$20,419). The first order condition in equation (2) indicates that \$51 is MWTP to avoid exposure to HTF or a lower bound economic cost of flood exposure. These costs encompass a range of financial and non-financial impacts, including, but not limited to, income losses or business disruptions (e.g., smaller foot traffic), loss of use value (e.g., inability to use a nearby park), health risks (e.g., due to limited access to healthcare facilities), and the costs of various compensating behaviors (e.g., increased commuting times due to road closures). Given that the average number of days with HTF in the sample is 5.6, the estimated coefficient suggests a 1.4% or \$286 decline in annual rent per unit.

Interestingly, larger floods do not seem to reduce rental rates (if anything, there seems to be a small positive effect). This is likely due to two reasons: first, larger floods might destroy housing stocks such that the supply of rental units might go down. Secondly, the quality of housing stock may go up after larger floods due to rebuilding or renovation. Such a noisy impact is in a stark contrast to economically large and statistically significant impacts of larger floods on mobility (Appendix Table B.2).

The result in column (1) might be implausible if the majority of renters are not well-informed about HTF, potentially due to being new residents in the area or due to the lack of saliency of HTF. However, the Survey of Income and Program Participation (SIPP) panel data suggests that the median (mean) duration of tenancy for renters in coastal states are 36 (64) months as of 2018, which implies that renters likely possess or acquire local knowledge, which they can use when selecting housing.[16] Further, high tide seems to be a salient issue in particular for coastal states. In Appendix Figure B.5 (a), we plot time series of Google search intensity for two keywords "high tide" and "flash flood" for the entire US. We find that over our sample period, search intensity for these two terms were comparable. Further, in Appendix Figure B.5 (b), we classify states into two groups based on the relative search intensity between these two keywords. It reveals that in almost all coastal states, "high tide" is searched more frequently than "flash flood," suggesting that high tide events hold a comparable level of attention among coastal residents as flash floods do for those in inland states.

The spillover effect in mobility documented in Figure 4.1 (f) suggests that even if a zip code is not directed affected by HTF, the utility of living in that zip code can still go down if HTF disrupts trips to places—although the magnitude can be smaller than the case where own zip code is inundated. In column (2), we test this by estimating the impact of HTF on rental rates for zip codes that are within 100km from the coastal line but not overlapping with the inundation map. Consistent with the conjecture, we find that one additional day of HTF reduces rental rates by 0.13%, which suggests that impaired mobility is one of the key drivers behind rental rates adjustments.

In column (3), we estimate the impact of HTF on the number of flood insurance claims per zip code to more rigorously test the impact of HTF on property damage. For this, because flood insurance claim has to be made within 60 days of damage, we use the number of days with HTF in the past two months as our key regressor (FEMA 2016). Consistent with Appendix Figure B.1 and Figure 4.1 (e), we find 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—if

[16] SIPP has been frequently used by the Census Bureau to study the duration of residence (Mateyka and Marlay 2010).

anything, the point estimate indicates a small negative impact. This is in a stark contrast to larger floods which cause 4.6 additional claims. While column (3) reassures that the impact of HTF on property damage is negligible, it is worth highlighting that \$51 reduction in rent would not reflect potential concern about property losses even if the estimated effect is positive. That is, because we use rental rates as opposed to the housing prices as an outcome variable, the financial risk of minor property damage caused by HTF is borne by landlord rather than a renter.[17]

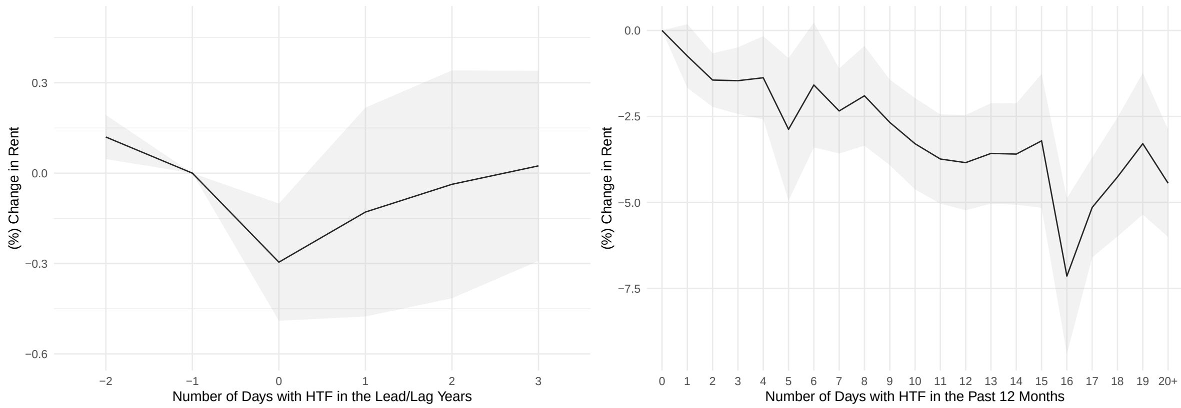
In column (4), we repeat the same exercise as column (3) for zip codes that are within 100km from the coastal line but not overlapping with the inundation map. Similar to column (3), HTF has no meaningful impact on flood insurance claims, which is not surprising given that these zip codes are not directly inundated by HTF.

As robustness checks, in Appendix Table B.3, we repeat the same exercise as Table 5.1 without including baseline controls. The results are strikingly similar—albeit minor differences in point estimates for columns (3) and (4)—, which further assures that the number of days with HTF is a plausibly exegenous variation.

In Figure 5.1 (a), we estimate a distributed lag model version of equation (5). Specifically, in addition to the N_{zmt}, we also include three lags (the number of days with HTF in the past 13-24, 25-36, and 37-48 months) and two lead (the number of days with HTF in the future 1-12 and 13-25 months) as regressors (practically, we omit the future 1-12 months category).[18] We find that future HTF exposure does not have impact on the current rental rates: the estimate for coefficient –2 (the number of days with HTF in the future 13-25 months) is close to zero and does not seem to have an evident pre-trend, which is consistent with the parallel trend assumption. Further, HTF exposure in the farther past does not affect the rental rate. For instance, one additional day with HTF in the past 13–24 (25–36) months reduce rental rates by (statistically insignificant) 0.13% (0.04%). This suggests that people do not seem to utilize information from farther past. Such a spike and decay pattern has been also documented with respect to flood insurance purchases after floods (Gallagher

[17]HTF may affect rental rates through asset losses channel if renters interpret increased HTF as an increased probability of large flood events, which may cause damage to their belongings (contents of a house). However, Lee and Zheng (2023b) finds that HTF has little impact on belief about climate change. In addition, potential asset losses on vehicles can be covered at a low cost by auto insurance–the average premium for a comprehensive auto insurance in the coastal states over the sample period (2015–2021) is \$160. Even if HTF increases chances of larger floods by a small percentage, the expected cost will be small (because the baseline probability of large floods is small).

[18]To make the model saturated, we drop about 1% of observation that did not have any HTF over the six years periods.



(a) Rental Impact by the Timing of HTF (b) Rental Impact by the Number of HTF Incidents

Figure 5.1: The Impact of HTF on Rental Rates by HTF Timing and Frequency. This plot shows how the price effect of the HTF varies by (a) the timing and (b) the frequency of HTF incidents. For (a), we regress leads and lags of HTF incidents on the log of rent. For (b), we regress the number of 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.

2014).

In Figure 5.1 (b), 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 $k \in \{0, 1, 2, \cdots, 19, 20+\}$. In this model, $k = 0$ serve as the baseline omitted category. Thus, the estimated coefficients for each bin indicates the additional rental rate impact when a zip code experiences k days of HTF as opposed to 0.

The estimated coefficients in Figure 5.1 (b) shows that rental rates gradually 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 curve indicates that a linear parameterization in Table 5.1 column (1) is a reasonable first order approximation.

Further, estimates in Panel (b) can be used for additional robustness check. In particular, Callaway et al. (2024) shows that equation (5) may suffer selection bias in the presence of heterogeneous treatment effect. To investigate to what extent this problem might bias our preferred treatment effect estimate in Table 5.1 column (1), we follow Callaway et al. (2024) and estimate the impact of one additional day of HTF on rental rates by calculating a frequency weighted average of first-differenced non-parametric estimates. That is, we calculate $\sum_{k=1}^{20}(\beta^k - \beta^{k-1})P(N = n_k|N > 0)$

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 0.31%, which indicates that Table 5.1 column (1) is a conservative estimate.

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 0.25% or $51 reduction in rent resulting from one additional day of HTF (Table 5.1 Column (1)) as a lower bound economic costs beyond asset losses associated with a day of flooding.[19] With this caveat, we multiply $51 by the number of households exposed to the PDD floods and by each events' duration.

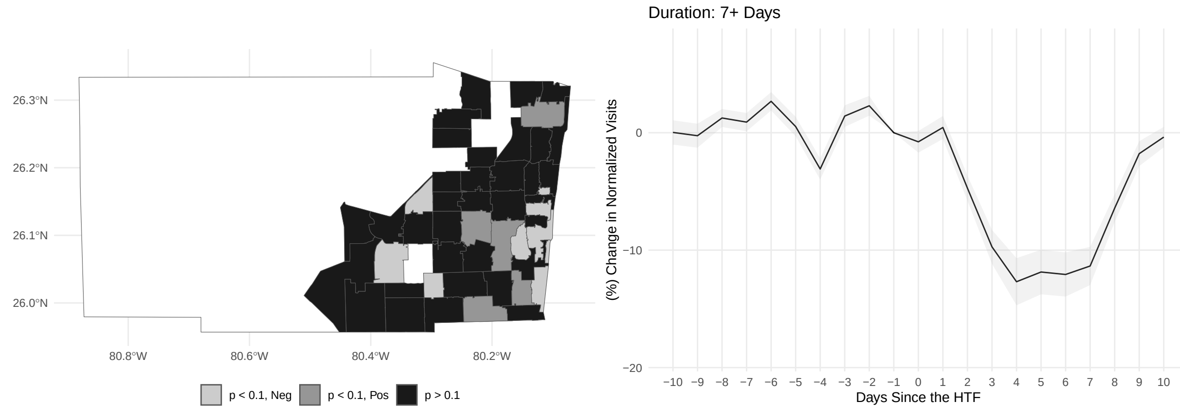
One potential approach to identify the number of households exposed to PDD is using location (county) information in FEMA's PDD database.[20] However, flood damage can be highly localized and some part of a county might not be affected by the event. Thus, we estimate zip code specific mobility impact due to a PDD to identify zip codes that are affected by the event. For this, we first list up zip codes that are located within the counties affected by for each PDD. Then, for each zip code, we compare the number of visits for PDD periods (the day of PDD and three daily lags) to the rest of days in the 2018–2021 period after controlling for daily precipitation, month, day of the week (e.g., Monday, Tuesday, etc), and year fixed effects while clustering standard errors at the fortnightly level.

Figure 6.1 (a), which is from Broward county in Florida, illustrates the importance of this approach.[21] Here, we classify zip codes into three categories: zip codes with statistically significant (at the 90% confidence level) negative impacts, statistically significant but positive impacts, and statistically insignificant impacts. Importantly, to prevent overestimation, we only treat households in the first group, which are 9 out of 47 zip codes in the Broward County case, as zip codes that are negatively affected by PDD. More generally, we find that 31% of zip codes that are included in PDD counties over the 2018–2021 period are negatively and statistically significantly affected by PDD

[19] 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.

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

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



(a) Mobility Impact of PDD for Broward County, FL

(b) Mobility Impact of 7+ days PDD

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 impact of PDD on mobility over time for PDD events with documented duration of 7+ days.

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 of the economic costs of PDD events. Using the number of households information from the American Community Survey, we find that for a typical year, 12.7 million households are residing in zip codes that are affected by PDD floods over the 2018–2021 period.

For the duration of an event, we leverage the "incident window" in the PDD dataset from FEMA after making a few adjustments. Because the 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 (FEMA 2022)—we first cap the incident window at a week to prevent overstating the duration. Further, we compare the incident window to an empirical flood duration, which we estimate using the Safegraph 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.[22] Figure 6.1 (b) shows the result for PDD with documented duration of 7+ days. We find that the negative mobility impact lasts for 11 days (including the day of event), which is longer than the documented incident window. Similarly, in Appendix Figure B.6 we present results for all incident window categories,

[22] Moderate and major event dummies, which are created using water level records from NOAA gauge stations are excluded because PDDs happen in inland areas as well.

which show that the incident window does not seem to overestimate the actual flood duration.

By multiplying $51 to the number of affected households and duration of each PDD, we find that the average economic cost of PDD over the 2018–2021 period is at least $4 billion per year. While acknowledging the underlying differences in methodologies, comparing $4 billion to the estimated asset losses from floods in the US ($32 billion) from Wing et al. (2022) underscores the potential significant underestimation of true flood costs when economic costs are disregarded. We highlight that $4 billion is likely 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.

7 Conclusion

While theoretically consistent cost of flooding is a welfare loss from the event, existing flood 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 events, to estimate the economic cost of floods that goes beyond the asset losses.

Using granular location data from mobile devices, we find direct evidence of disruptions caused by HTF: on the day of the event, the number of visits per POI declines by 5% for zip codes that are inundated. Interestingly, zip codes that are within 100km from the coastal line, but are not inundated still experience a 3.6% reduction in number of trips, which suggests a large spillover effect. Further, using zip code level rental rates data, we show that being exposed to one additional day of HTF in the past 12 months reduces rents by 0.25% or $51 per day. Given the nature of HTF, which primarily disrupts various dimensions of daily lives and economic activities rather than incurring asset losses, we interpret this as the economic cost of floods.

Using this parameter as a lower bound of economic cost from larger floods, we show that economic costs from PDD floods over the 2018–2021 period is at least $4 billion per year. Our findings suggest that ignoring indirect costs can substantially underestimate the true cost of floods.

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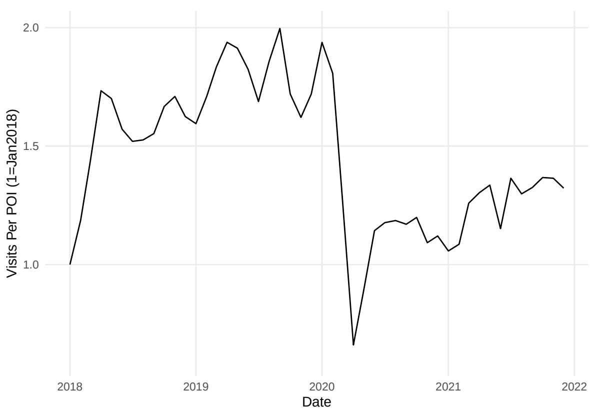
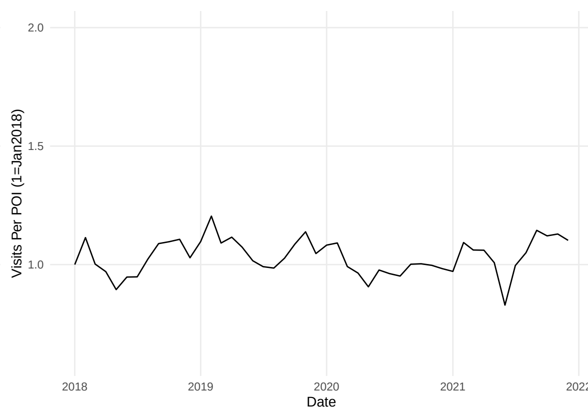
A Measurement Issues with the Safegraph Data

Safegraph collects location data from roughly 10% of mobile devices in the US (Parolin and Lee 2021). While this data allow analyzing mobility in an unprecedented detail, previous research has pointed out at least three different measurement issues. First, Safegraph collects location information using the mobile GPS positioning process. This inherently generates measurement error because its accuracy is guaranteed only at the 5 meters level. This implies that the GPS positioning might not be able to distinguish whether a user is in one store or another especially in dense urban areas (Knittel et al. 2023). However, we believe that this is a less of a concern especially when our attention is understanding the average number of visits to any POI at the zip code level. This could be more problematic when we explore the industry specific effect, but even in that case, industry classifications are broad enough to mute measurement errors from the GPS positioning process.

Another caveat is that the data represents a subset of population who have a smartphone and who have agreed to share their location. Consequently, specific demographic groups with limited smartphone access, such as elderly or low-income individuals, may be underrepresented in the data. This implies that our estimates on the impact of HTF on visit counts should be interpreted as a lower bound because these demographic groups are more vulnerable to floods including HTF.



(a) Raw Visit Counts



(b) Normalized Visit Counts

Figure A.1: 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.

Lastly, the 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). Appendix Figure A.1 (a) plots the average number of visits per POI over time using the raw data using January 2018 as the baseline. The time series shows that the number of visits has increased substantially in the first half of 2018. The number continues to grow before it plummeted in early 2020 due to the pandemic. There is a rebound over time, but even by the end of 2021, the number of visits is 1.5 times of the baseline, which is substantially lower than the pre pandemic period. Such a dramatic change in time series could be driven by a range of factors such as changes in the sample of cellphone devices used for data collection (Kurmann and Lalé 2022).

To account for this issue, we follow Kurmann and Lalé (2022) and divide the daily number of visits per POI by the number of cellphone devices per census block group. Then, we aggregate the data to the zip code level. Figure A.1 (b) depicts the normalized visit counts for all POIs, which is substantially smoother than Figure A.1 (a).

B Additional Tables and Figures

Table B.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.

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Table B.2: Effect of High-Tide Flooding on Mobility

	(1)	(2)	(3)	(4)	(5)	(6)
Lead 7	-0.5815***	-0.0008	-0.1786***	-0.0208***	-0.2238***	-0.2618
	(0.1532)	(0.0060)	(0.0421)	(0.0072)	(0.0604)	(0.2030)
Lead 6	0.0768	0.0025	0.0158	0.0152**	-0.0762**	0.2544*
	(0.1109)	(0.0029)	(0.0291)	(0.0068)	(0.0305)	(0.1439)
Lead 5	-0.5709***	-0.0036	-0.1529***	-0.0064	-0.2767***	-0.5325***
	(0.1123)	(0.0034)	(0.0331)	(0.0067)	(0.0420)	(0.1799)
Lead 4	-0.4018***	-0.0086***	-0.0894**	-0.0247***	-0.1505***	-0.0967
	(0.1166)	(0.0033)	(0.0364)	(0.0078)	(0.0365)	(0.1939)
Lead 3	-0.2132	-0.0041	0.0047	-0.0221**	-0.0246	0.0241
	(0.1690)	(0.0036)	(0.0479)	(0.0091)	(0.0438)	(0.1959)
Lead 2	-0.4384***	-0.0063*	0.0134	-0.0174*	-0.1012***	7.31e-5
	(0.1132)	(0.0034)	(0.0377)	(0.0089)	(0.0376)	(0.1557)
HTF	-2.740***	-0.0294***	-0.6355***	-0.0840***	-0.7125***	-1.880***
	(0.2090)	(0.0041)	(0.0517)	(0.0091)	(0.0824)	(0.3219)
Lag 1	-0.6608***	-0.0023	-0.0969**	-0.0025	-0.2460***	-0.6641***
	(0.1417)	(0.0031)	(0.0389)	(0.0072)	(0.0461)	(0.2047)
Lag 2	-0.4202***	-0.0040	-0.0398	-0.0013	-0.2227***	0.0357
	(0.1443)	(0.0032)	(0.0386)	(0.0070)	(0.0545)	(0.1947)
Lag 3	-0.2488	-0.0043*	-0.0527	-0.0077	-0.0902	-0.1460
	(0.1962)	(0.0024)	(0.0513)	(0.0090)	(0.0650)	(0.2292)
Lag 4	-0.8207***	-0.0037	-0.2576***	-0.0303***	-0.1439***	-0.7365***
	(0.1640)	(0.0037)	(0.0439)	(0.0082)	(0.0504)	(0.2314)
Lag 5	-0.3984***	0.0022	-0.0636**	-0.0033	-0.0397	-0.4826***
	(0.1172)	(0.0034)	(0.0273)	(0.0083)	(0.0314)	(0.1450)
Lag 6	0.0602	0.0023	0.0328	-0.0012	0.0240	0.0906
	(0.1113)	(0.0022)	(0.0273)	(0.0061)	(0.0400)	(0.2155)
Lag 7	0.0723	0.0036	0.0360	0.0004	-0.0322	0.0591
	(0.1171)	(0.0029)	(0.0304)	(0.0061)	(0.0363)	(0.1569)
Moderate Flood	-6.867***	-0.0421***	-1.526***	-0.1544***	-1.701***	-3.200***
	(0.7267)	(0.0113)	(0.1955)	(0.0298)	(0.2408)	(0.7152)
Major Flood	-10.02***	-0.0747**	-3.966***	-0.2705*	-2.527***	-10.26***
	(2.448)	(0.0345)	(0.8366)	(0.1477)	(0.6436)	(1.931)
Dep. Var Mean	55.4	0.6	14.5	1.8	13.7	52.2
Dep. Var	All	Auto	Retail	Restaurant	Doctor Visits	All
Sample	Inund	Inund	Inund	Inund	Inund	No Inund
Observations	2,105,505	2,105,505	2,105,505	2,105,505	2,105,505	2,585,895

Note:
This table corresponds to Figure 4.1 (a). For the interest of space, only 7 leads and lags are presented. Coefficients are multiplied by 1000 for readability. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

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Table B.3: Effect of High-Tide Flooding on Rental Rates and Flood Insurance Claims (w/o Controls)

	(1)	(2)	(3)	(4)
Dependent Var.:	log(Rent)	log(Rent)	Claim Ct	Claim Ct
N Days with HTF (Past 12 Months)	-0.0025***	-0.0013***		
	(0.0004)	(0.0005)		
N Days with HTF (Past 2 Months)			0.0976	-0.0843
			(0.1119)	(0.0846)
Sample	Inundated	No Inund	Inundated	No Inund
Fixed-Effects:				
Zip Code	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Year by County	Yes	Yes	Yes	Yes
Observations	119,507	147,579	119,507	147,974

Note:
This table presents the impact of recent HTF exposure on rental rates (columns (1) and (2)) and flood insurance claims (columns (3) and (4)). Baseline controls are 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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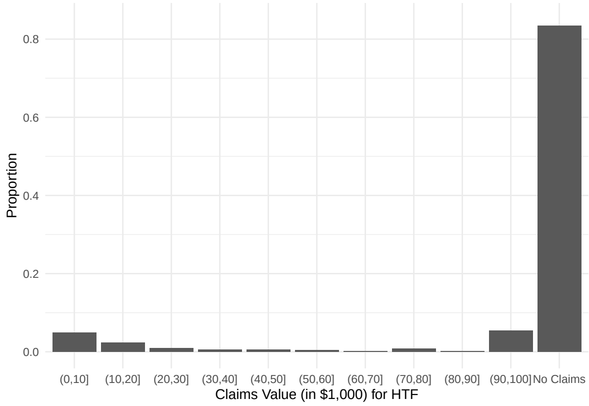
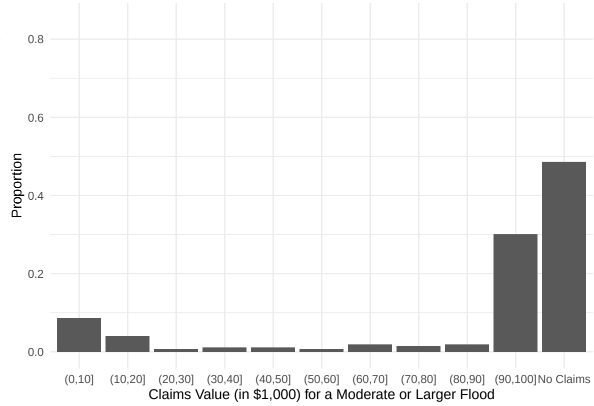


(a) Claims Value (in 1,000 dollars) for HTF (Minor Floods)



(b) Claims Value (in 1,000 dollars) for Moderate or Major Floods

Figure B.1: The Distribution of NFIP Claims (in 1,000 dollars) for Different Flood Sizes. Panels (a) and (b) show the distribution of NFIP claim size (in 1,000 dollars) at the community level for HTF and larger floods between Jan 2015 and Jun 2022. Claims values are capped at 100,000 dollars for readability.

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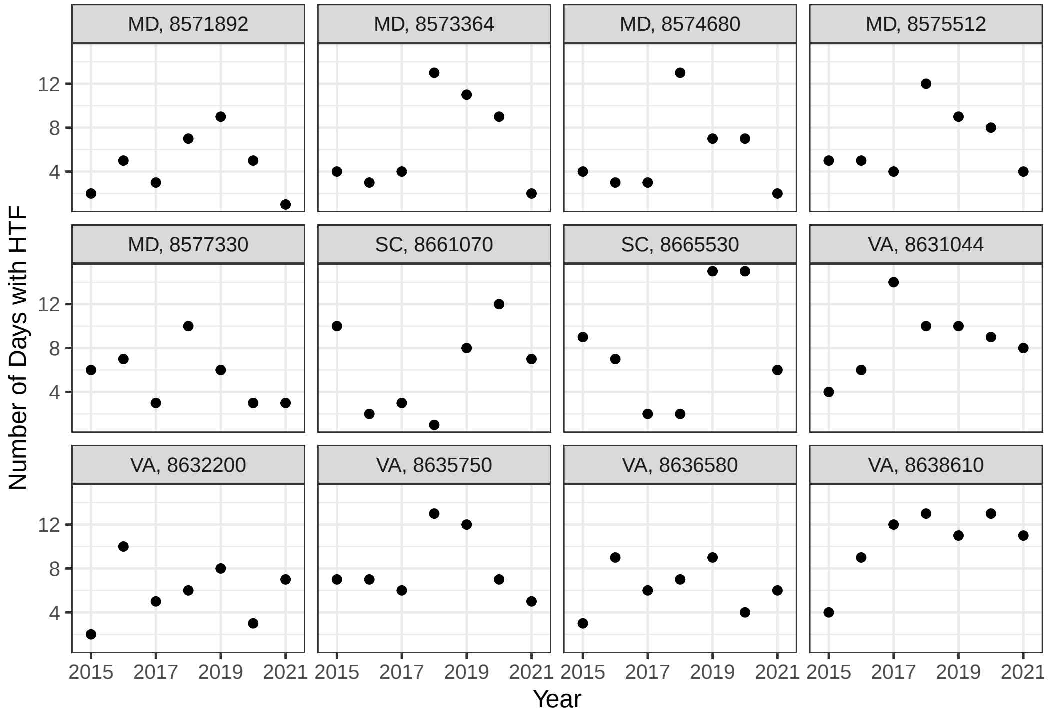

Figure B.2: The Number of Days with HTF for Sites Located in Maryland, South Carolina, and Virginia. These figures document the number of days with HTF for each gauge station located in Maryland, South Carolina, and Virginia.

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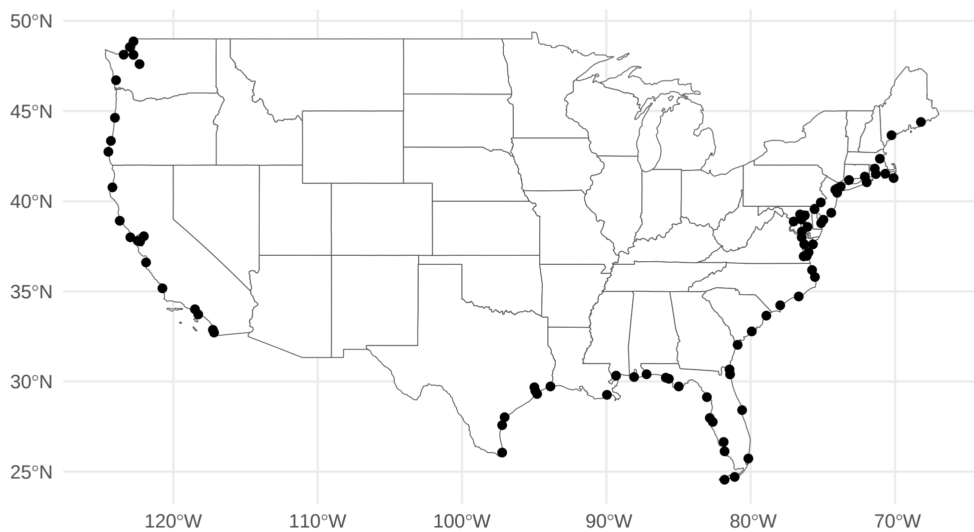

Figure B.3: Location of NOAA Gauge Stations. This figure depicts 84 NOAA gauge stations within the contiguous US that has flood thresholds from Sweet et al. (2018).

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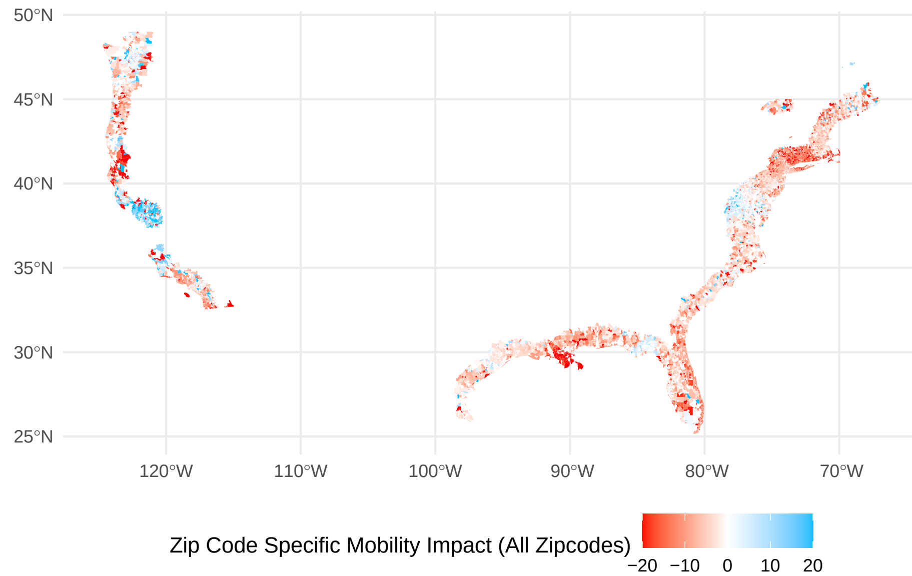
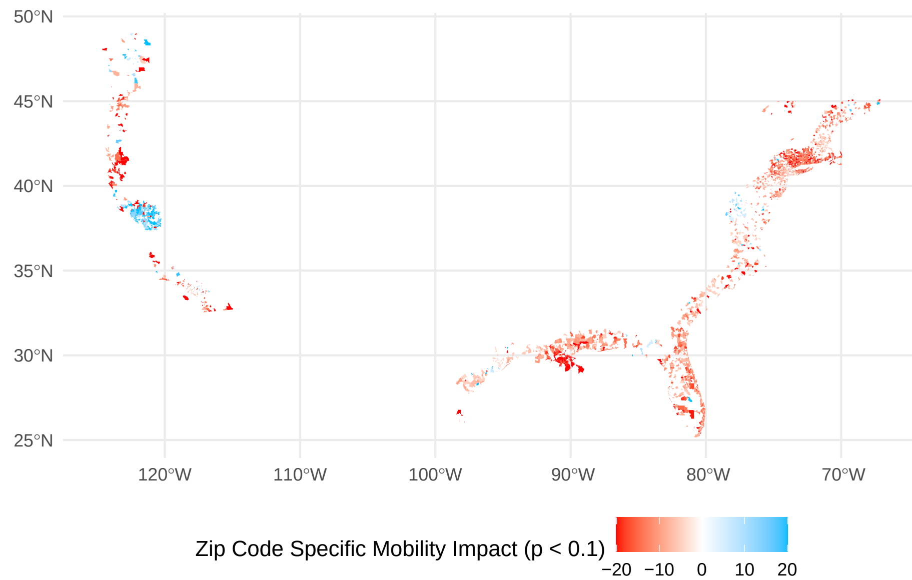


(a) All Zip Codes



(b) Zip Codes with Statistically Significant Impact

Figure B.4: Coastal Zip Codes Affected by HTF. These maps depict zip code specific impact of HTF on mobility for coastal zip codes (within 100km from the coastal line) for the contiguous US. For this, we estimate zip code specific impact of HTF using equation (4). Panel (a) shows all zip codes and Panel (b) keep ones that are statistically significant at the 90% confidence level.

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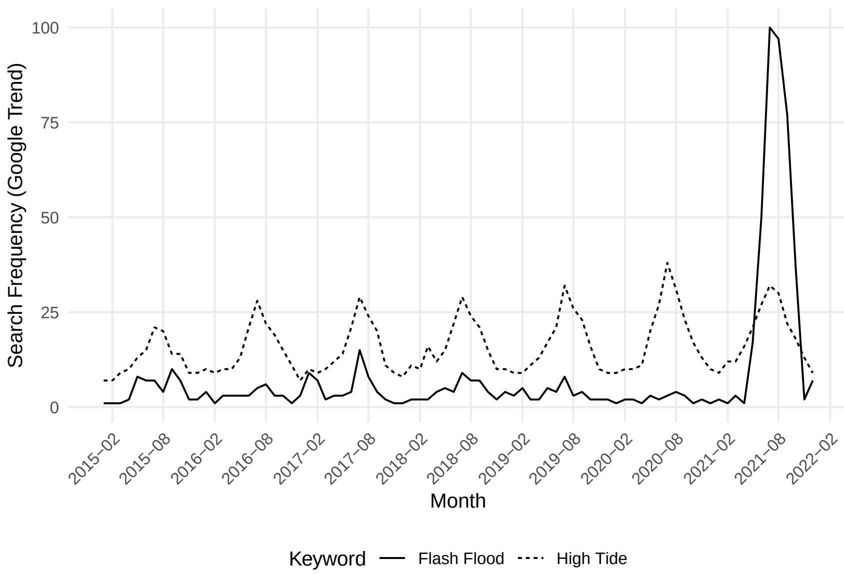
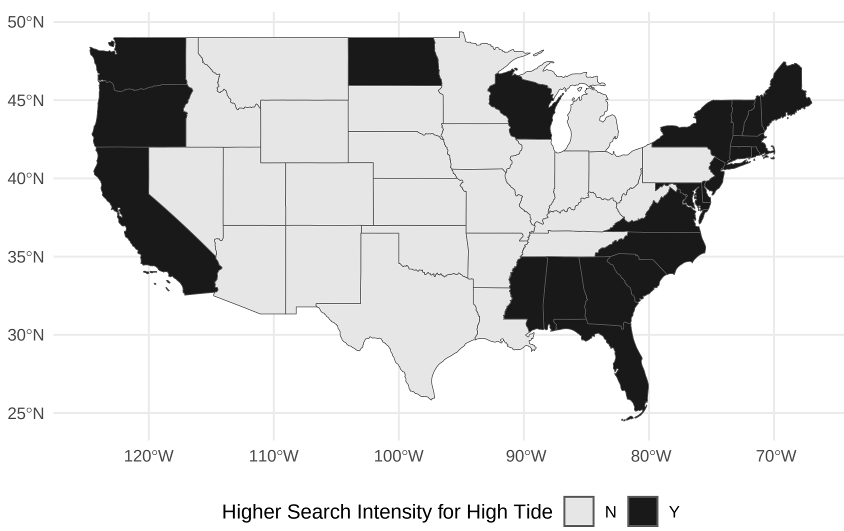


(a) Google Search Intensity for the Entire US



(b) State Specific Search Intensity

Figure B.5: HTF and Awareness. These figures show (a) Google search trends for high tide and flash flood for the entire US and (b) state specific relative search intensity for these two keywords.

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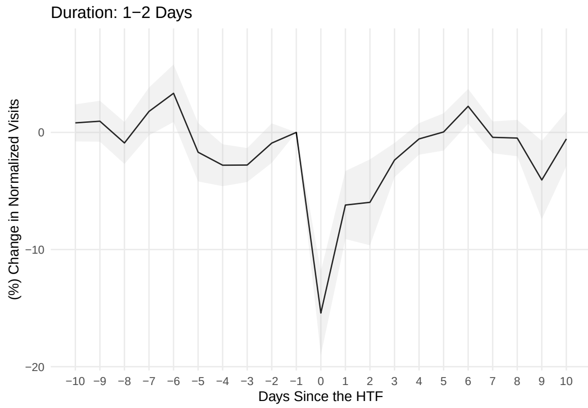
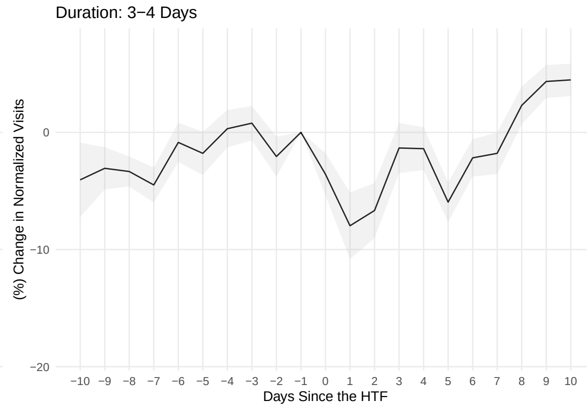
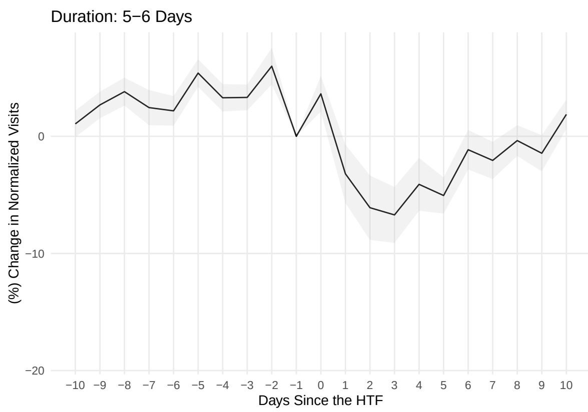


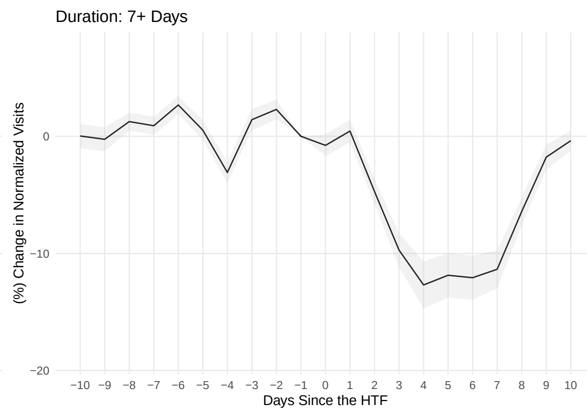
(a) 1- and 2-day PDD Flood



(b) 3- and 4-day PDD Flood



(c) 5- and 6-day PDD Flood



(d) 7+ day PDD Flood

Figure B.6: The Effect of PDD Floods on the Number of Daily Visits. 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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