The Cost of Hurricane Evacuations

Jacob Gellman, Hannah Hennighausen, Brett Watson, Kevin Berry*

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Abstract

Climate change is increasing the frequency of extreme natural disasters, which threaten human life and safety. Evacuation is a key protective action against hurricane danger, but it may be costly for individuals. Despite being an important input to emergency management decisions, there is little evidence on the size of these costs. In this paper we estimate the welfare costs of hurricane evacuations. We combine spatial data on hurricanes, flooding, and evacuation orders with millions of records of individuals' cell phone-derived movement activity to study how communities behave during hurricanes. These data generate rich insights about evacuation behavior, including differences by physical risk, information provision, and demographics. Using a structural travel cost model we estimate that the welfare costs of evacuation can be large when compared to mortality costs, averaging a ratio of one to ten but occasionally exceeding the value of statistical life lost (VSL). These results document an understudied cost of hurricanes.

Keywords: Hurricanes, natural disasters, evacuations, information, climate change
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*Jacob Gellman is in the Department of Economics, University of Alaska Anchorage (jgellman@alaska.edu). Hannah Hennighausen is in the Department of Economics, University of Alaska Anchorage (hbhennighausen@alaska.edu). Brett Watson is in the Institute of Social and Economic Research, University of Alaska Anchorage (bwjordan2@alaska.edu). Kevin Berry is in the Department of Economics, University of Alaska Anchorage (kberry13@alaska.edu). We thank Andrew Plantinga and Margaret Walls for comments and suggestions on this paper. We are also grateful to seminar participants at the AERE session of the Western Economics Association 2024 Conference. This research was funded in part by the Rasmuson Foundation.

1 Introduction

Hurricanes have caused more than $340 billion in direct damages in the United States since 2018 (NOAA NCEI 2024). These disasters pose substantial risks to human life and safety. Mortality can account for a high share of hurricane damages, with the value of statistical life lost (VSL) frequently in the hundreds of millions of dollars for a given storm, especially for tail events. These tail events will likely become more common as hurricanes grow in frequency and intensity under climate change (Balaguru et al. 2023; Sobel et al. 2016).

One of the key protective actions against hurricane danger is evacuations. Understanding the costs and benefits of evacuation is crucial for public policy, since the direct expenditures of evacuation can be costly (Whitehead 2003). Further, individuals depend on government information to know when to leave (Thompson, Garfin, and Silver 2017). A risk-neutral emergency manager should issue an evacuation order when the expected avoided costs of mortality exceed the costs of evacuation. This decision relies on knowledge of the costs of evacuation; however, few estimates of these costs exist. While high-quality survey work has investigated individuals' direct expenditures for evacuations (Whitehead 2003), no work has empirically valued the welfare costs of evacuation.

In this paper, we investigate the costs of hurricane evacuations. We combine spatial data on hurricanes, flooding, and evacuation orders with tens of millions of records of individuals' cell phone-derived movement activity to study how communities behave during hurricanes. Using a structural travel cost demand model, we provide the first empirical estimates of the welfare costs of hurricane evacuations.

Our analysis proceeds in several steps. First, using data on foot traffic, we provide descriptive evidence of individuals' avoidance of hurricane-affected areas, as well as substitution of activities to unaffected areas. Avoidance behavior increases with measures of hurricane severity, such as wind speed or flooding, as well as for informational mechanisms such as higher category storms and National Weather Service (NWS) alerts. Descriptively, reductions in activity are strongest in whiter, more educated, higher income, and more urban areas. These analyses build confidence in the use of cell phone-derived mobility data to measure the effects of hurricanes on movement patterns.

Next, we develop a structural model of an individual's decision to evacuate during a hurricane. Utility depends on the choice to move throughout space, the average utility of a destination, the cost to reach it, and hurricane conditions at the origin or destination. Using a log shares transformation as in Berry, Levinsohn, and Pakes (1995), we linearize the model, which allows for computationally feasible estimation of utility parameters from nearly 44 million observations of origin-destination movement flows. This transformation, to our knowledge, has not been applied in a travel cost setting using aggregated data.

We generate several insights about evacuation behavior. Individuals show positive willingness to pay (WTP) to evacuate from hurricane-affected locations. These costs are much larger for communities subject to mandatory evacuation orders; and, consistent with prior literature, we find that individuals are unresponsive to voluntary evacuation orders (Younes, Darzi, and Zhang 2021). Similarly, although NWS alerts are associated with declines in overall foot traffic, we find no evidence that individuals' evacuation decisions respond to this form of information provision. Comparing effect sizes, WTP is nearly twice as large with a mandatory evacuation order as with no order or a voluntary order. In demographic heterogeneity analyses, we find that higher income communities and more educated communities are most responsive to mandatory evacuation orders. Effects by race are mixed, consistent with results from past survey literature (Huang, Lindell, and Prater 2016; Thompson, Garfin, and Silver 2017). Notably, although the effects of mandatory orders are strong, no demographic group responds to voluntary evacuation orders at a level that is statistically different than receiving no order.

In back-of-the-envelope calculations, we apply the empirical WTP estimates over affected populations to determine the total cost of hurricane evacuations by storm. This calculation separately considers the welfare costs for areas subject to voluntary orders, mandatory orders, or no order. Total costs range from \$11 million to more than \$120 million per storm. Evacuation costs are generally increasing for higher category storms, as these hurricanes tended to have had a greater number of evacuation orders. To contextualize the estimates, we compare them to the property damages and mortality costs of hurricanes. For most storms, evacuation costs are small when compared to total property damage. More germane to emergency management is the comparison to mortality costs. We find that the cost of evacuation can be large when compared to mortality costs, averaging a ratio of one to ten but occasionally exceeding total VSL, particularly for less-damaging storms that had a high rate of evacuation. While tempting to judge that these areas were overly evacuated, these comparisons do not provide conclusions about the optimality of evacuation for any one storm, which would require knowledge about the counterfactual loss of life; nevertheless, the figures provide context as to the magnitude of these costs. Overall, we consider our estimates to be conservative, as they do not measure additional evacuation expenses such as lodging.

There are several contributions of this study. First, it contributes to a sparse literature on the cost of hurricane evacuations, which has been identified as an important information gap for emergency managers (Lindell, Prater, and Peacock 2007). Whitehead (2003) estimated the opportunity costs of hurricane evacuation, surveying residents in North Carolina about revealed preference expenditures following Hurricane Bonnie in 1998, as well as stated preference expenditures under hypothetical scenarios. Depending on storm intensity and emergency management, Whitehead (2003) estimated total evacuation costs at between $1.8 and $91 million per storm, which is in the range of welfare costs for the twelve hurricanes we study.[1] Mozumder and Vásquez (2015) found similar per-household costs following Hurricane Ike in Texas. These studies do not directly estimate counterfactual expenditures in the absence of evacuation, but provide a useful basis for comparison. To our knowledge, no study has measured the welfare costs of hurricane evacuations using observational data.

We also add to the evidence on community behavior during hurricanes and disasters. There has been substantial work in the survey literature to understand why individuals do or do not comply with evacuation orders, focusing on physical measures of risk, demographic predictors, information provision, and past experience (Huang, Lindell, and Prater 2016; Thompson, Garfin, and Silver 2017). Our results are broadly consistent with this survey literature. Among studies using observational data, our work is complementary to research using cell phone-derived movement data in applications to wildfire smoke (Burke et al. 2022; Fitzgerald 2024; Holloway and Rubin 2023; Lee and Beatty 2024) and in descriptive case studies of two hurricanes (Juhász and Hochmair 2020; Li, Qiang, and Cervone 2024; Yabe

1. These numbers are inflation-adjusted to 2023 dollars from original published estimates of $1 to $50 million in 1999 dollars.

and Ukkusuri 2020; Younes, Darzi, and Zhang 2021). Further, our study is related to an economics literature studying pre-disaster preparation and the value of forecasting (Beatty, Shimshack, and Volpe 2019; Molina and Rudik 2024).

Lastly, we contribute to a recent literature that values environmental costs using large, administrative datasets (Earle and Kim 2024; Gellman, Walls, and Wibbenmeyer 2023; Newbold et al. 2022). Interest is growing in the use of large datasets to estimate structural utility parameters; however, doing so can present computational challenges (Earle 2022). Some researchers have therefore focused on methods which recover individual-level parameters using aggregated data (Melstrom and Reeling 2024). Our study is the first to apply the Berry, Levinsohn, and Pakes (1995) framework in a travel cost setting to value environmental costs or benefits with aggregated data.

The remainder of this paper is organized as follows. Section 2 describes the data and discusses institutional detail surrounding hurricane evacuations. In Section 3, we provide reduced form evidence on reductions in total activity during a hurricane, as well as substitution to nearby areas. Section 4 develops a structural model of hurricane evacuation, provides empirical estimates of welfare costs, and gives insights into evacuation behavior. In Section 5 we apply these estimates to back-of-the-envelope calculations of the total cost of hurricane evacuations by storm. Section 6 concludes.

2 Data

We combine data on hurricanes, flooding, government alerts, and cell phone-derived movement patterns to create two estimating datasets. The first dataset is a panel of monthly total foot traffic at a Census block group level over the years 2018 to 2023. These data show how overall activity in an area changes during the month of a hurricane. The second dataset focuses on flows of movement from origin block groups to destination counties, where the unit of observation is an origin-destination pair by month for the years 2018 to 2023. These paired movement flows are used to structurally estimate the cost of hurricane evacuation.

2.1 Cell phone mobility data

To understand mobility patterns during hurricanes, we draw from a database of cell phone-based geolocation information from the data provider Advan, a database which was formerly managed by SafeGraph.[2] Cell phone-derived movement data have been used to understand responses to wildfire smoke (Burke et al. 2022; Fitzgerald 2024; Holloway and Rubin 2023; Lee and Beatty 2024) and in descriptive case studies of two hurricanes (Juhász and Hochmair 2020; Li, Qiang, and Cervone 2024; Yabe and Ukkusuri 2020; Younes, Darzi, and Zhang 2021). These cell phone data have been shown to be broadly representative of the US population, both spatially and demographically, and are consistent with survey-based estimates of mobility patterns (Squire 2019; Kang et al. 2020).

Movement data are collected from smartphone apps using location-based services. Over the study period of 2018 to 2023, the sample represents an average of 32.5 million unique devices per month in the United States. Device visits are recorded to approximately 7 million unique "Points of Interest" (POIs), which represent identifiable commercial, industrial, public, or other locations.[3] We draw from Advan's Neighborhood Patterns dataset, which aggregates information to a Census block group by month level. We observe both an intensive margin of visitation, as measured by the total number of stop counts anywhere in the block group, as well as an extensive margin for the number of unique devices observed by home block group of origin, a measure which does not account for intensity of visitation.[4]

The mobility data come with some limitations. First, the database covers the period from 2018 through the present, which narrows the set of hurricanes we may study. The data also have limited coverage for residential locations, which prevents a detailed study of sheltering in place during a hurricane. In addition, for privacy reasons, Advan implements some censoring rules when low visitor counts are observed from an origin location.[5] These concerns should

2. Data were acquired from: Dewey. 2024. https://www.deweydata.io.

3. Some frequently observed POIs include restaurants, medical facilities, religious organizations, urban transit systems, recreation or sport centers, gas stations, hair or nail salons, schools, automotive shops, offices, grocery stores, warehouses, and retail stores.

4. Advan determines each device's home location by identifying the location where the device spent the most time between 6pm and 8am during the previous calendar month.

5. Specifically, if a POI received only one visitor from a particular Census block group, the visit is added to the total number of stop counts, but the block group is not reported; if two to four visitors are observed from a block group, it is reported as having four visitors.

be mitigated in our analysis because the Neighborhood Patterns data aggregate information to a block group by month level, making it less likely that origin locations are censored.

We limit attention to the eight coastal southeast states spanning from Texas to North Carolina. The first empirical analysis in Section 3 measures total foot traffic, i.e. the intensive margin of stop counts, at a block group by month level over the years 2018 to 2023, resulting in approximately 3.7 million observations. The second empirical analysis in Section 4 measures visitation from origin block groups to destination counties. We restrict the data to the months of June through November over 2018 to 2023, resulting in approximately 44 million block group to county paired observations.

2.2 Hurricanes and flooding

To measure the location and timing of hurricanes, we collect spatial data from NOAA's National Hurricane Center (NHC) Best Track Data (HURDAT2).[6] These data report, at six hour intervals, the path of a hurricane, as well as wind speed radii associated with 34-, 50-, and 64-knot winds. They also contain information on intensity, which measures peak wind speed during the interval, and the Saffir-Simpson scale hurricane category (Tropical Storm and Category 1 through 5). Figure A1 in the appendix plots an example of the raw points and radii data. We match these data to block groups and record the maximum wind speed and category during the month.

While hurricane polygons measure exposure, they do not measure the level of impact or damage to a location. To identify severe hurricanes, we collect data on FEMA presidential disaster declarations at a county level.[7] We follow the procedure of Roth Tran and Wilson (2023) and restrict attention to "Major Disasters" which were either coded as a "hurricane" or which contained the word "hurricane" or "tropical storm" in the declaration title. Treatment timing is determined based on the incident date, rather than the declaration date, which can occur much later.[8]

6. NOAA NHC. 2024. "NHC Data in GIS Formats." https://www.nhc.noaa.gov/gis.

7. FEMA. 2024. "OpenFEMA Dataset: Disaster Declarations Summaries - v2." https://www.fema.gov/openfema-data-page/disaster-declarations-summaries-v2.

8. Presidential disaster declarations are a formal process by state and local governments to request federal assistance after a disaster that exceeds their response capabilities. The declaration date of a disaster can occur months after the incident date. For more discussion, see Roth Tran and Wilson (2023) or OpenFEMA.

As an additional measure of physical impacts, we identify block groups exposed to flooding using FEMA National Flood Insurance Program (NFIP) claims data.[9]. In the data, each claim is geolocated to a block group with an associated loss date. Block groups are coded as flooded if there is at least one claim during the month. One important limitation of this measure is that we cannot observe flooding in block groups where there are no NFIP insurance policies.

Lastly, we use information from NOAA NCEI, which reports total property damages and deaths attributable to a storm.[10] These statistics generate useful comparisons for the empirical estimates of hurricane evacuation costs.

2.3 NWS alerts and evacuation orders

Government-provided information plays a key role in individuals' evacuation decisions. Under the Protective Action Decision Model (PADM) framework used by emergency management researchers, individuals form perceptions about physical characteristics of storms based on messaging from the NWS that is transmitted through local authorities, the media, and peer networks (Huang, Lindell, and Prater 2016). This model implies that information filters through several pathways before reaching an individual. For example, Iman et al. (2023) document how local emergency managers rely heavily on NWS forecasting and communication in their decision-making over evacuation orders. While local emergency managers may have more proximate communication with affected individuals, they are downstream from NWS information provision (Freeman et al. 2021).

To explore these upstream information channels, we collect data on NWS alerts from Iowa Environment Mesonet.[11] We identify block groups that received a NWS alert by overlaying polygon shapefiles of temporally-explicit watches, warnings, and advisories for hurricanes. NWS issues forecasts and alerts for public zones which are, in most cases, identical to counties. However, zones are frequently subset into smaller geographic areas when there are

9. FEMA. 2024. "OpenFEMA Dataset: FIMA NFIP Redacted Claims - v2." https://www.fema.gov/openfema-data-page/fima-nfip-redacted-claims-v2.

10. NOAA NCEI. 2024. "Billion-Dollar Weather and Climate Disasters." https://www.ncei.noaa.gov/access/billions/.

11. Iowa State University. 2024. "Iowa Environment Mesonet." https://mesonet.agron.iastate.edu/request/gis/watchwarn.phtml.

large differences in weather due to topography or proximity to water. Figure A2 displays an example of the raw data for 2019. Visually, zones are smaller when near to the coast.

We are also interested in downstream information channels, namely, evacuation orders. When discussing evacuation orders, the terms "voluntary" and "mandatory" reflect the probability of exposure and severity of hurricane impacts.[12] These terms carry different legal implications that may affect a resident's decision to evacuate.[13] The literature has documented that individuals comply much more strongly with mandatory evacuation orders than with voluntary evacuation orders (Freeman et al. 2021; Thompson, Garfin, and Silver 2017; Younes, Darzi, and Zhang 2021). This disparity is significant because residents who delay evacuation may substantially increase their risk.

We gather information on voluntary and mandatory hurricane evacuation orders from the Hurricane Evacuation Order Database (HEvOD) (Anand, Alemazkoor, and Shafiee-Jood 2024). This database compiles records of evacuation orders with linked sources to communications made in traditional news and social media. Evacuation orders are distinguished as voluntary or mandatory, and are assigned to a location based on county FIPS code. In total, we compile information for more than 400 unique evacuation orders. Since many areas receive both voluntary and mandatory orders, i.e. when a voluntary order is upgraded to a mandatory order, we reclassify treatment under mutually exclusive categories. If an area received both a voluntary and a mandatory order, we code it as mandatory; if it received only a voluntary order, we code it as voluntary.

2.4 Demographics

To explore demographic moderators, we match Census Bureau data at a block group level.[14] Relevant variables include race, education, and income, as well as measures of urban development. The cell phone mobility data defines block groups based on 2010 Census geographies,

12. FEMA defines a "voluntary evacuation" as a warning that "a threat to life and property [...] is likely to exist in the immediate future," and a "mandatory evacuation" as a warning that "imminent threat to life and property exists." See: FEMA. 2024. "Glossary of Terms." https://www.fema.gov/pdf/plan/glo.pdf.

13. For example, in some states, officials have limited liability when responding to emergency calls made during a mandatory evacuation order. See: National Governors Association. 2024. "Governor's Guide to Mass Evacuation." https://www.nga.org/wp-content/uploads/2018/08/GovGuideMassEvacuation.pdf.

14. United States Census Bureau. 2024. https://data.census.gov.

which were effective during the years 2010 through 2019. Where available, we use American Community Survey data for the year 2018, which was the first year of our study period.[15]

2.5 Travel cost

We calculate driving distances and driving times between origin block groups and destination counties using the Open Source Routing Machine (OSRM), which combines routing algorithms with road network data from OpenStreetMap.[16] These calculations rely on population-weighted centroids for origin and destination geometries. Based on past survey evidence, we restrict attention to driving distances within 500 miles to preclude the possibility of air travel, which would complicate the calculation of travel cost (English et al. 2018). These restrictions result in 4.8 million unique routes.

Following English et al. (2018), we calculate travel costs between block group z and county j in month and year t according to:

$$c_{zjt} = p^D_{zt} D_{zj} + p^T_{zt} T_{zj}, \tag{1}$$

for travel distance D_{zj} and travel time T_{zj}. The variable p^D_{zt} captures the per-mile travel cost between block group z and county j, which includes gasoline costs, per-mile vehicle maintenance, and per-mile marginal vehicle depreciation. To estimate per-mile gasoline costs, we combine monthly information on gasoline prices with annual nationwide average fuel economy estimates.[17,18] Per-mile vehicle maintenance costs and marginal depreciation are sourced from AAA data.[19,20] Finally, we compute hourly costs of travel time p^T_{zt} as one-third the average household income in the block group's zip code tabulation area divided by

15. An exception is our measure of "proportion of urban population," which relies on the 2010 Decennial Census, since 2020 Census geometries would not correspond to these block groups.

16. OSRM. 2024. "osrm: Interface Between R and the OpenStreetMap-Based Routing Service OSRM." https://cran.r-project.org/web/packages/osrm/index.html.

17. Energy Information Administration. 2024. "Weekly Retail Gasoline and Diesel Prices." https://www.eia.gov/dnav/pet/pet_pri_gnd_a_epmr_pte_dpgal_m.htm.

18. Bureau of Transportation Statistics. 2024. "Average Fuel Efficiency of US Light Duty Vehicles." https://www.bts.gov/content/average-fuel-efficiency-us-light-duty-vehicles.

19. For example: AAA. 2018. Your Driving Costs 2018. https://exchange.aaa.com/wp-content/uploads/2018/09/18-0090_2018-Your-Driving-Costs-Brochure_FNL-Lo-5-2.pdf.

20. Marginal depreciation cost is computed as the difference between "reduced depreciation" and "increased depreciation" between 10,000 and 20,000 miles, divided by 10,000 miles, as in English et al. (2018).

2,080 working hours per year (English et al. 2018). All travel costs are inflation-adjusted to 2023 dollars.

2.6 Descriptive features of the data

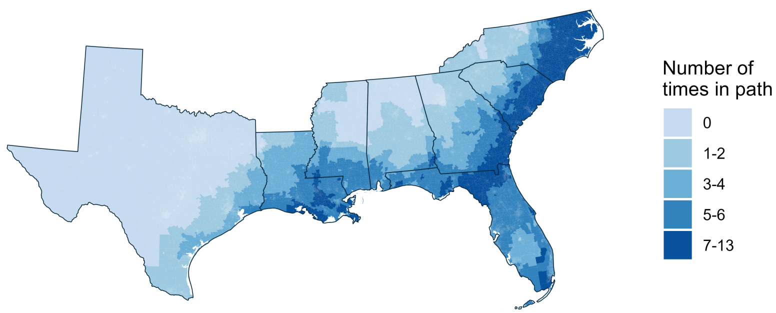
We analyze the evacuation behavior of individuals, aggregated at the block group level, in response to hurricanes and evacuation orders. The analysis considers various measures of treatment, including being physically in the path of a hurricane, receiving a county-level disaster declaration, and experiencing a voluntary or mandatory evacuation order.

Figure 1 provides a visualization of the frequency of treatment over the study period of 2018 to 2023. Panel (a) shows the number of times that a block group experienced a tropical storm of any category, where the category is measured at the time of intersection with the block group. For most block groups in the Southeast it is the norm to have experienced a tropical storm. However, only coastal areas experienced a Category 3 or greater hurricane over the time period, as shown in panel (b). Panel (c) displays an alternative measure of treatment in county-level FEMA presidential disaster declaration. This variable, although subject to institutional decision-making, serves as a measure of the severity of damages; by comparison to panel (a), disaster declaration is far less frequent. Panel (d) visualizes the intersection of panels (a) and (c), showing a block group's ever-treated status for various combinations of hurricane measures. The empirical analysis considers the varying measures of treatment both jointly and separately.

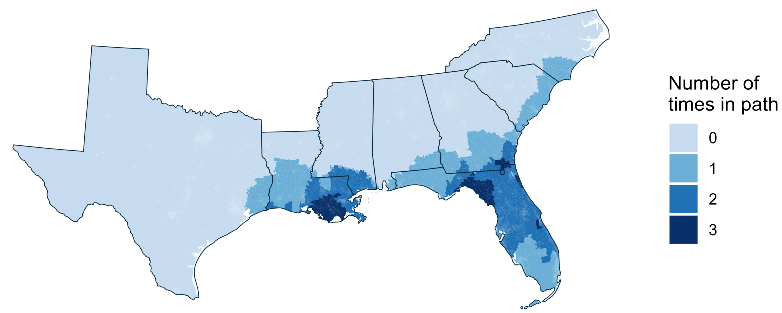
Table 1 summarizes the variation in the data by individual storm. We observe seventeen hurricanes of Category 1 or greater and twenty other tropical storms. As in Figure 1, the reported category measures the maximum category we observe at the time of intersection with a block group; for example, although Hurricane Michael reached Category 5 before landfall, by the time it touched Florida it had weakened to a Category 4 storm. For each storm, the table reports the number of block group by month observations that experienced evacuation orders, received county disaster declarations, or were ever in the path of the hurricane. Over 2018 to 2023, the resulting dataset contains 51,073 unique block groups, 839 unique counties, and approximately 3.7 million block group by month observations, with more than 177,000 observations that fell in the path of a hurricane.

Figure 1: Hurricane frequency over 2018 to 2023

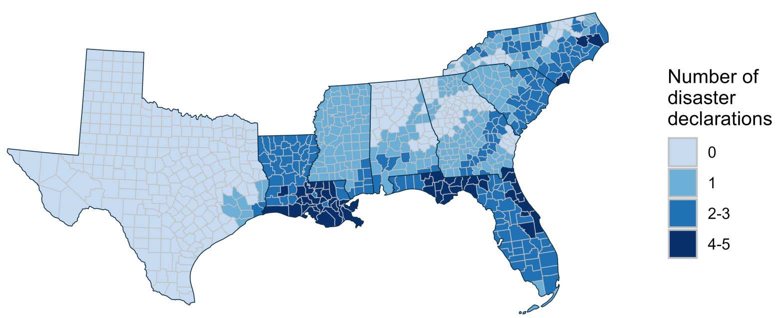
(a) Hurricane path, any Cat.



(b) Hurricane path, Cat. 3 or greater



(c) Disaster declarations



(d) Ever-treated

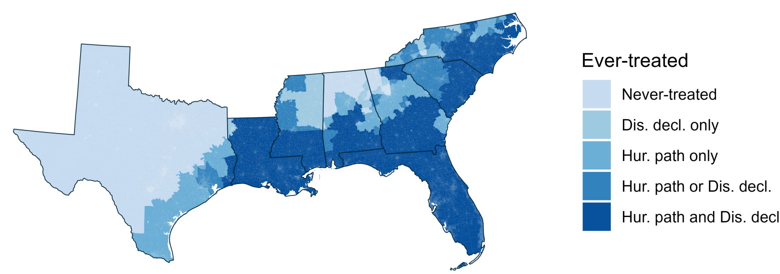


Table 1: Variation in hurricane path, category, evacuation order, and disaster declaration

Storm	Cat.	Year	Obs w/ Vol. Evac.	Obs w/ Man. Evac.	Obs w/ Dis. Decl.	Obs In Path
Ian	5	2022	496	3,602	11,801	18,065
Dorian	4	2019	404	4,186	1,095	5,594
Ida	4	2021	569	1,051	3,071	3,430
Idalia	4	2023	781	3,062	6,462	10,748
Laura	4	2020	3,113	1,511	2,260	2,408
Michael	4	2018	717	737	1,933	6,369
Delta	3	2020	813	1,199	2,214	4,080
Zeta	3	2020	237	33	1,783	8,935
Florence	2	2018	140	1,454	3,642	5,230
Sally	2	2020	811	1,124	1,340	2,112
Barry	1	2019	943	548	2,054	3,180
Elsa	1	2021	195	0	0	6,926
Eta	1	2020	208	76	0	10,690
Hanna	1	2020	68	0	0	1,026
Isaias	1	2020	1,175	134	0	5,623
Nicholas	1	2021	18	178	0	3,756
Nicole	1	2022	1,024	1,348	10,792	13,434
Other tropical storms (N=20)	0		0	0	4	44,495
Treated						177,071
Untreated						3,499,598
Total						3,676,669

Notes: Observations represent block groups by month. Category reports the maximum Saffir-Simpson category achieved by a storm while over land. Voluntary and mandatory evacuations are categorized to be mutually exclusive, such that the voluntary column reports observations which did not also receive a mandatory evacuation. Disaster declarations are measured at a county level. A block group is considered in the path of a storm if it saw sustained winds greater than 39 mph.

3 Avoidance

Before proceeding to the structural estimation, we examine reduced form evidence on changes in total activity during the month of a hurricane. We estimate changes to foot traffic for areas directly in the path of a hurricane as well as for areas that experienced spillovers in visitation. These analyses shed light on avoidance of hurricane-affected locations and substitution to unaffected areas. They also build confidence in the use of mobile device data to measure the effects of hurricanes on movement patterns.

3.1 Empirical approach and identification

For each block group we observe the raw number of visits to all POIs in a given month, which will serve as the dependent variable. This variable measures the intensity of activity for a given area. We estimate changes to activity based on two measures of treatment. First, we identify areas that were physically in the path of a hurricane using the NOAA best track polygons. Second, we record whether a block group's county received a FEMA presidential disaster declaration.

We expect that foot traffic drops for a block group in the path of a hurricane, and that it drops more strongly when the block group's county also received a disaster declaration, since these events were more severe. It is reasonable to expect that this estimation produces spillovers; individuals within an affected area will substitute their activities to areas outside the hurricane zone, and individuals from outside the area who would have visited will substitute to unaffected regions. To capture this spillover, we include an indicator for block groups whose county received a disaster declaration but which were not in the actual path of a hurricane. These block groups are likely to be near to a hurricane-affected area but may not have experienced as significant of damage. In this sense, the uninteracted disaster declaration variable captures spillovers to less-affected areas, while the interacted disaster declaration variable isolates severely-affected areas.

For block group z in month and year t, we estimate:

$$\log(\text{visits}_{zt}) = \varphi \ \text{hur\_path}_{zt} + \ \theta \ \text{dis\_decl}_{zt} + \vartheta \ (\text{hur\_path}_{zt} \times \text{dis\_decl}_{zt}) + \delta_z + \lambda_t + \eta_{it}, \tag{2}$$

where visits_{zt} measures observed foot traffic count, hur_path_{zt} is an indicator if the block group was in the path of a hurricane, and dis_decl_{zt} is an indicator if the block group's county received a presidential disaster declaration. In addition, the vector X'_{zt} measures other characteristics of the block group, such as disaster alerts or other information. Block group fixed effects δ_z account for location-specific, time-invariant unobservables, while month by year fixed effects λ_t capture time-varying unobservables that are common to all block groups. Regressions are weighted by block group population and standard errors are clustered at a county level.

We expect that $\varphi < 0$ and $\vartheta < 0$ due to the adverse effects of hurricanes, while $\theta > 0$ due to spillovers in proximate or less-affected regions. Identification requires an assumption that foot traffic would have evolved in a parallel fashion as compared to unaffected areas, conditional on fixed effects. It also requires that we adequately capture spillovers with the uninteracted dis_decl_{zt} variable. The inclusion of many control units, with more than 50,000 unique block groups and nearly 3.5 million untreated observations (see Table 1), should mitigate this concern.

3.2 Changes in total activity during a hurricane

Table 2 displays results from estimation of Equation 2. Column 1 shows that the coefficients follow the expected sign. Block groups in the path of a hurricane experience an approximately 2.7 percent reduction in activity. We also find evidence supporting the use of the uninteracted dis_decl_{zt} variable as a measure of spillover, as block groups whose counties received disaster declarations but which were not in the path of a hurricane experienced an increase of 4.7 percent in foot traffic. The reduction in activity is strongest for block groups both in a hurricane path and receiving a disaster declaration, where the addition of all three estimated coefficients implies a 5.7 percent reduction in activity.

Table 2: Changes to foot traffic during a hurricane

	(1)	(2)
Hurricane path	-0.0273*	-0.0273*
	(0.0153)	(0.0152)
Disaster decl.	0.0466***	0.0464***
	(0.0097)	(0.0097)
Hurricane path × Disaster decl.	-0.0765***	-0.0723***
	(0.0194)	(0.0210)
Hurricane path × Disaster decl. × Vol. evac. order		0.0343
		(0.0216)
Hurricane path × Disaster decl. × Man. evac. order		-0.0327*
		(0.0181)
Block group FE	Yes	Yes
Month-year FE	Yes	Yes
Observations	3,658,837	3,658,837

Notes: A block group is considered in the path of a storm if it saw sustained winds greater than 39 mph. Disaster declarations are measured at a county level. Voluntary and mandatory evacuations are treated as mutually exclusive, such that areas coded as receiving a voluntary evacuation did not also receive a mandatory evacuation. Standard errors are clustered by county. Weights are by block group population. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Column 2 interacts indicators equal to one if an area was subject to a voluntary or mandatory evacuation order. The coefficient for voluntary evacuations is insignificant, implying no measurable difference in activity for hurricane-affected areas that either received a voluntary evacuation order or no evacuation order. In contrast, the marginal effect of a mandatory evacuation order is an additional 3.3 percent reduction in foot traffic, for a total effect of 8.6 percent, though the coefficient for the marginal effect is significant only at the 10 percent level.

The variables for evacuation orders may capture information effects, but they may also be correlated with hurricane intensity. Appendix B explores physical mechanisms, alternative information treatments, and demographic responses. Reductions in foot traffic are stronger for higher measures of physical severity, such as wind speed and flooding. Reductions are also stronger for whiter, more educated, higher income, and more urban areas. Examining alternative informational mechanisms, effects are larger for areas that saw NWS hurricane alerts or higher category hurricanes. Taken together, these results build confidence in the use of mobility data to measure changes in human movement during a hurricane.

It is worth re-emphasizing that reductions in foot traffic are likely driven both by outmigration of the block group's own residents and by avoidance from individuals outside the area. To focus specifically on evacuation, we turn to an analysis that uses paired origin-destination observations. These models allow for estimation of the cost of hurricane evacuations.

4 Evacuation

In this section we model an individual's decision to evacuate during a hurricane. Utility is derived from an individual's choices to move throughout space, choices which depend on the average utility of a location, the travel cost to reach it, and hurricane conditions at the origin or destination. We empirically estimate these utility parameters to derive the welfare damages of hurricane evacuation.

4.1 Modeling approach

At time t, an individual i chooses whether to visit geographic location j. Define utility as:

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt}, \tag{3}$$

where V_{ijt} denotes the observable portion of utility, and ε_{ijt} is a preference parameter known to the individual but unobserved by the econometrician. Let V_{ijt} be specified as:

$$V_{ijt} = \begin{cases} \alpha c_{ijt} + \beta h_{jt} + \delta_j + \lambda_t + \xi_{z(i),j,t}, & j \in \{1, 2, ..., J\}; \\ \phi h_{z(i),t} + X'_{z(i),t}\gamma + \delta_{z(i)}, & j = 0, \end{cases} \tag{4}$$

where $z(i)$ corresponds to individual i's home zone, such as a block group. Several variables capture mean utility, including constants for destination locations δ_j, home zones $\delta_{z(i)}$, and time λ_t. The variable $\xi_{z(i),j,t}$ represents a random preference parameter at the level of home zone by destination by time, and is unobserved by the econometrician. Of interest to the researcher is the variable c_{ijt}, which denotes the travel cost of person i to visit location j at time t, and from which one can infer the marginal disutility in expenditure α. In addition, the vector $X'_{z(i),t}$ includes other explicit characteristics of the home zone, such as disaster alerts or other information. The variables h_{jt} and $h_{z(i),t}$ summarize hurricane conditions at the home zone or destination location. The parameter of interest is the WTP to move from a hurricane-affected origin to an unaffected destination, WTP $= \phi/\alpha$.

Under the assumption that ε_{ijt} is distributed iid type I extreme value, the probability that individual i visits location j is:

$$\mathbb{P}_{ijt} = \frac{\exp(V_{ijt})}{\exp(V_{i0t}) + \sum_{k=1}^{J} \exp(V_{ikt})}. \tag{5}$$

To estimate, consider a market shares approach as in Berry, Levinsohn, and Pakes (1995). Group representative individuals i into their home zone z, such as their home block groups. For every location j, origin zone z, and time t, the estimated share of individuals choosing j is given by:

$$s_{zjt} = \frac{\exp(V_{ijt})}{\exp(V_{i0t}) + \sum_{k=1}^{J} \exp(V_{ikt})}. \tag{6}$$

Taking logs, we have:

$$\log(s_{z0t}) = V_{i0t} - \log(\exp(V_{i0t}) + \sum_{k=1}^{J} \exp(V_{ikt}))$$

$$\log(s_{z1t}) = V_{i1t} - \log(\exp(V_{i0t}) + \sum_{k=1}^{J} \exp(V_{ikt}))$$

$$...$$

$$\log(s_{zJt}) = V_{iJt} - \log(\exp(V_{i0t}) + \sum_{k=1}^{J} \exp(V_{ikt})). \tag{7}$$

Differencing these logged shares yields a linear equation:

$$\begin{aligned}\log(s_{zjt}) - \log(s_{z0t}) &= V_{ijt} - V_{i0t} \\ &= \alpha c_{ijt} - \phi h_{z(i),t} + \beta h_{jt} - X'_{z(i),t}\gamma + \delta_j - \delta_{z(i)} + \lambda_t + \xi_{z(i),j,t}. \qquad (8)\end{aligned}$$

Under the assumption that $\xi_{z(i),j,t}$ is distributed normally, Equation 8 can be estimated using ordinary least squares. The share s_{z0t} is coded as the share of individuals choosing the home location, such that effects are measured based on differences in utility relative to home.

4.2 The utility of evacuation

We estimate Equation 8 using flows of travel from origin block group z to destination county j in month and year t. An observation consists of a block group origin and county destination pair for a given month and year. Travel flows are measured based on whether unique devices were observed in a location and thus do not reflect the intensity of activity, but rather the presence or absence of a visitor from a given location. We define the origin zone as hurricane-affected if the block group was both in the path of a hurricane and received a disaster declaration, taking a value of one or zero. A destination county is defined as hurricane-affected if it received a hurricane disaster declaration, again taking a value of one or zero.

We restrict the data in two ways. First, because almost all of the observed hurricanes and tropical storms occurred during the months of June to November, we restrict attention to these months for the years 2018 to 2023. Second, we limit attention to origin-destination pairs that are within 500 miles of driving distance, as described in Section 2.5.[21] The estimating dataset consists of 43,908,471 observations.

Identification requires that the effect of hurricanes and travel cost be exogenous conditional on fixed effects that control for average traits of individuals by origin zone, unobserved qualities of each destination location, and time-varying factors common to all groups. Conditional on these fixed effects, which capture unobservables such as sorting by preferences or

21. English et al. (2018) show that, in the context of recreational travel to the Gulf Coast, individuals are likely to have traveled by air when coming from more than 500 miles, which complicates interpretation of the travel cost variable.

beliefs, the effect of hurricanes is treated as exogenous.[22] Parameters of interest are constant across individuals, which comes from an assumption of preference homogeneity. However, we explore potential preference heterogeneity over hurricane exposure and evacuation orders using observable demographic and economic variables for origin block groups. Lastly, although evacuation orders are subject to institutional decision-making, as discussed in Section 2.3, the receipt of this information is treated as plausibly exogenous from the perspective of individuals.

Table 3 displays results from estimation of Equation 8. In all regressions, observations are weighted by origin block group population, with standard errors clustered at a county level to allow for arbitrary correlation of the error term for nearby block groups. WTP is computed based on the ratio of the marginal disutility of hurricane exposure to the marginal disutility of expenditure, where standard errors use the delta method.

Column 1 reports the main estimation, which focuses on the disutility of hurricane exposure. Coefficients yield the expected sign. Individuals are less likely to make trips to locations at greater distances, as indicated by the negative and statistically significant travel cost coefficient. They are also more likely to move from hurricane-affected areas to safe locations, as indicated by the positive and statistically significant coefficient for hurricane conditions at the origin. The third coefficient suggests some avoidance of hurricane-affected destinations for individuals in safe origin areas, but it is not statistically significant. The interacted variable for hurricane conditions at both origin and destination is noisy and close to zero. WTP for evacuation, which measures an average over the population, is estimated at approximately \$7 per person.

Column 2 interacts indicator variables for voluntary and mandatory evacuation orders at the origin location. Individuals appear unresponsive to voluntary evacuation orders, as indicated by a small and noisy coefficient for the marginal effect of a voluntary evacuation order. Effects are largely driven by mandatory evacuation orders, as WTP in column 2 is significant only for hurricane exposure under mandatory evacuation. According to this estimate, WTP is approximately \$11 per person when under mandatory evacuation.

22. See, for example, Bakkensen and Barrage (2022) for a discussion of the effect of beliefs on sorting and the capitalization of flood risk into home prices.

Table 3: Marginal utility in evacuation

	(1)	(2)
Travel cost (dollars)	-0.0062***	-0.0062***
	(0.0001)	(0.0001)
Hurricane (orig.)	0.0424**	0.0347
	(0.0213)	(0.0239)
Hurricane (dest.)	-0.0138	-0.0137
	(0.0090)	(0.0090)
Hurricane (orig.) × Hurricane (dest.)	0.0056	0.0052
	(0.0293)	(0.0295)
Hurricane (orig.) × Vol. evac.		-0.0023
		(0.0266)
Hurricane (orig.) × Man. evac.		0.0338*
		(0.0193)
WTP: Hurricane	6.84**	
	(3.45)	
WTP: Hurricane, No evac.		5.59
		(3.87)
WTP: Hurricane, Vol. evac.		5.23
		(4.84)
WTP: Hurricane, Man. evac.		11.05***
		(3.83)
Block group orig. FE	Yes	Yes
County dest. FE	Yes	Yes
Month-year FE	Yes	Yes
Observations	43,908,471	43,908,471

Notes: An origin block group is considered hurricane-affected if it saw sustained winds greater than 39 mph and received a disaster declaration. A destination county is considered hurricane-affected if it received a disaster declaration. Voluntary and mandatory evacuations are categorized to be mutually exclusive, such that areas coded as receiving a voluntary evacuation did not also receive a mandatory evacuation. WTP is computed based on the ratio of the marginal disutility of hurricane exposure to the marginal disutility of expenditure, with standard errors using the delta method. General coefficient standard errors are clustered by origin county. Weights are by origin block group population. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Individuals may differ in their responsiveness to hurricanes and evacuation orders. Table 4 explores demographic heterogeneity by interacting quartile bins for race, education, and income with evacuation orders. The prior survey literature has found mixed results regarding heterogeneity of evacuation by race (Huang, Lindell, and Prater 2016; Thompson, Garfin, and Silver 2017). Table 4 shows some evidence that non-white communities are more responsive to mandatory evacuation orders, however there is not a clear trend when examining heterogeneity by Black and Hispanic groups specifically. Higher income and more educated groups show monotonically increasing responses with higher quartile bins, consistent with results in Yabe and Ukkusuri (2020) and Younes, Darzi, and Zhang (2021). Notably, according to these results, no group is responsive to voluntary evacuation at a level that is statistically different than receiving no evacuation.

Appendix C reports additional heterogeneity analysis. WTP is increasing with the measured wind speed of a hurricane, reaching \$25 per person for the strongest wind speeds. Though not monotonic, effects are also generally larger for higher category storms, where category is measured by the maximum strength of the storm rather than by the experienced wind of a block group. Testing an alternative form of information provision than evacuation orders, we also find no statistically different response when communities receive NWS alerts.

Table 4: Marginal utility in evacuation, demographic responses to evacuation orders

	(1)	% Black (2)	% Hispanic (3)	% White (4)	% Bachelor Deg. (5)	Med. Inc. (6)
Main effects						
Travel cost (dollars)	-0.0062***	-0.0062***	-0.0062***	-0.0062***	-0.0062***	-0.0062***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Hurricane (orig.)	0.0347	0.0346	0.0355	0.0346	0.0345	0.0357
	(0.0239)	(0.0239)	(0.0239)	(0.0239)	(0.0239)	(0.0238)
Hurricane (dest.)	-0.0137	-0.0137	-0.0137	-0.0137	-0.0137	-0.0132
	(0.0090)	(0.0090)	(0.0090)	(0.0090)	(0.0090)	(0.0089)
Hurricane (orig.) × Hurricane (dest.)	0.0052	0.0055	0.0043	0.0053	0.0056	0.0032
	(0.0295)	(0.0295)	(0.0295)	(0.0295)	(0.0295)	(0.0294)
Hurricane (orig.) × Vol. evac	-0.0023					
	(0.0266)					
Hurricane (orig.) × Man. evac	0.0338*					
	(0.0193)					
Voluntary evacuation orders						
Hurricane (orig.) × Vol. evac order × Het. Lowest Q		0.0043	-0.0219	-0.0111	0.0063	0.0231
		(0.0361)	(0.0249)	(0.0272)	(0.0222)	(0.0261)
Hurricane (orig.) × Vol. evac order × Het. 2Q		-0.0016	-0.0549	0.0034	0.0040	0.0037
		(0.0349)	(0.0388)	(0.0227)	(0.0270)	(0.0270)
Hurricane (orig.) × Vol. evac order × Het. 3Q		-0.0099	0.0139	0.0192	-0.0088	-0.0203
		(0.0221)	(0.0308)	(0.0285)	(0.0304)	(0.0373)
Hurricane (orig.) × Vol. evac order × Het. Highest Q		-0.0023	0.0401	-0.0287	-0.0074	0.0009
		(0.0251)	(0.0261)	(0.0417)	(0.0492)	(0.0345)
Mandatory evacuation orders						
Hurricane (orig.) × Man. evac order × Het. Lowest Q		0.0215	0.0435*	0.0412	0.0030	0.0276
		(0.0213)	(0.0244)	(0.0280)	(0.0251)	(0.0242)
Hurricane (orig.) × Man. evac order × Het. 2Q		0.0362	0.0269	0.0431**	0.0177	0.0276
		(0.0221)	(0.0300)	(0.0190)	(0.0233)	(0.0256)
Hurricane (orig.) × Man. evac order × Het. 3Q		0.0517**	0.0216	0.0346	0.0480**	0.0354*
		(0.0201)	(0.0210)	(0.0219)	(0.0215)	(0.0206)
Hurricane (orig.) × Man. evac order × Het. Highest Q		0.0232	0.0447**	0.0227	0.0526**	0.0360*
		(0.0287)	(0.0188)	(0.0244)	(0.0223)	(0.0202)
Block group orig. FE	Yes	Yes	Yes	Yes	Yes	Yes
County dest. FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	43,908,471	43,908,471	43,908,471	43,908,471	43,904,188	42,864,164

Notes: Demographic heterogeneity is measured by quartile for the origin block group. An origin block group is considered hurricane-affected if it saw sustained winds greater than 39 mph and received a disaster declaration. A destination county is considered hurricane-affected if it received a disaster declaration. Voluntary and mandatory evacuations are categorized to be mutually exclusive, such that areas coded as receiving a voluntary evacuation did not also receive a mandatory evacuation. Standard errors are clustered by origin county. Weights are by origin block group population. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5 Total Cost of Hurricane Evacuation

We generate back-of-the-envelope calculations for the total cost of hurricane evacuation using the empirical WTP estimates of Table 3. We apply estimates according to whether a block group was hurricane-affected and whether it received a voluntary or mandatory evacuation order.[23] Because the empirical estimates represent an average WTP, we apply the welfare cost to the adult population of a block group based on the above definitions of treatment. These estimates consider only the costs within the eight states of the study area. In addition, estimates are specific to travel costs and do not account for individuals' additional direct expenditures, such as lodging and food costs (Whitehead 2003). In that sense, the estimates should be viewed as conservative.

Table 5 displays the welfare costs of evacuation by storm. These costs range from $11 million to more than $120 million per hurricane, with total costs over the period 2018 to 2023 amounting to half a billion dollars. For comparison, we also report each storm's total property damage, the associated deaths, and VSL using NOAA NCEI data. This exercise reveals several insights. First, evacuation costs are generally greater for higher category storms, as these storms tend to have had a greater number of observations subject to evacuation orders, as reported in Table 1. In most cases, the costs of evacuation are small when compared to the total property damage. Of relevance for emergency management is the comparison of evacuation costs to mortality costs. In some cases the cost of evacuation is substantial when compared to mortality costs, exceeding one fifth of the VSL or even surpassing the mortality costs entirely. On average, the ratio of evacuation costs to mortality costs is about one to ten.

These comparisons are presented for contextualization and do not provide definitive conclusions about the optimality of evacuation in any particular case. A risk-neutral emergency manager should issue an evacuation order, which is a discrete action, when the cost of evacuation is less than the expected avoided costs of evacuation, a calculation which depends on information about the likelihood of mortality from a storm. Thus, while it is tempting to conclude that storms such as Hurricane Nicole or Hurricane Idalia were overly evacuated since their evacuation costs exceeded their mortality costs, such a conclusion would require knowledge of the expected costs had these areas not been evacuated. Still, the estimates of Table 5 provide context for the magnitude of evacuation costs.

23. Voluntary and mandatory evacuation orders are treated as mutually exclusive. Areas are coded as receiving a voluntary evacuation order only if they did not also receive a mandatory order. If an area received a voluntary order and then subsequently received a mandatory order, it is coded as mandatory.

Table 5: Costs of hurricane evacuation compared to property damages and VSL

Storm	Cat.	Year	Cost of evac. (millions)	Property damage (millions)	Evac. as percent of property (%)	Deaths	VSL (millions)	Evac. as percent of VSL (%)
Ian	5	2022	120.3	114,774	0.10	152	1,702	7.1
Nicole	1	2022	97.3	1,044	9.32	5	56	173.8
Idalia	4	2023	73.7	3,430	2.15	5	56	131.7
Dorian	4	2019	64.8	1,912	3.39	10	112	57.9
Florence	2	2018	37.5	28,969	0.13	53	594	6.3
Ida	4	2021	22.9	81,945	0.03	96	1,075	2.1
Michael	4	2018	18.4	30,092	0.06	49	549	3.4
Laura	4	2020	17.4	27,215	0.06	42	470	3.7
Delta	3	2020	17.0	3,355	0.51	5	56	30.4
Barry	1	2019	14.8	713	2.07	2	22	65.9
Zeta	3	2020	11.8	5,093	0.23	6	67	17.6
Sally	2	2020	11.4	8,516	0.13	5	56	20.4
Total			507.3	307,057	0.17	430	4,816	10.5

Notes: Category denotes the maximum category achieved by the storm at landfall. Welfare losses from evacuation are calculated by applying the average WTP estimates of Table 3 to the adult population that was treated by a given hurricane and any associated evacuation orders. Voluntary and mandatory evacuation orders are treated as mutually exclusive such that if an area received both voluntary and mandatory orders, it is coded as a mandatory evacuation. Property damage and death statistics are taken from NOAA NCEI data. VSL denotes the value of statistical life lost based on a value of $11.2 million in 2023 dollars. All monetary damages are stated in 2023 dollars.

6 Conclusion

This study provides the first estimates of the welfare costs of hurricane evacuations. We combine spatial data on hurricanes, emergency management decisions, and cell phone-derived movement activity to study community behavior in response to evacuation orders. Using a structural travel cost framework, we estimate that the costs of hurricane evacuations range from $11 million to $120 million per storm. When compared to mortality costs, evacuation costs average a ratio of one to ten, but can be much higher and occasionally exceed the total VSL of a storm.

We make several contributions to the literature. First, we fill a critical information gap regarding the cost of hurricane evacuations, which is a key input to emergency management decisions (Lindell, Prater, and Peacock 2007). In addition, we add to the evidence on behavioral responses to hurricanes and disaster warnings, distinguishing between mechanisms related to physical risk, information sources, and demographic predictors. Lastly, we demonstrate an application of the Berry, Levinsohn, and Pakes (1995) framework in a travel cost setting to structurally value environmental costs.

We have spoken to a few key literatures, but it is worthwhile to further situate this work in the broader literature on hurricane costs. Evacuations represent a short-term cost, as do property damages. We can contrast these costs with other medium- and long-run economic effects of hurricanes, including impacts to labor markets, GDP, migration, or personal finance (Boustan et al. 2020; Deryugina 2017; Deryugina, Kawano, and Levitt 2018; Gallagher and Hartley 2017; Groen, Kutzbach, and Polivka 2020; Roth Tran and Wilson 2023; Strobl 2011). Some of these effects build over time, such as the use of government transfers (Deryugina 2017), while others may show non-linear dynamics, such as employment (Roth Tran and Wilson 2023). We expect that evacuations represent a purely short-term cost.

Our study carries some limitations. In a technical sense, we do not measure additional direct expenditures from evacuations, such as lodging. In a large survey, Whitehead et al. (2000) found that, during Hurricane Bonnie in 1998, around 16 percent of evacuees stayed in a hotel or motel, 6 percent stayed in a shelter, and 70 percent stayed with friends or family. For a hypothetical future scenario, 24 percent reported that they would stay in a hotel or motel, 12 percent in a shelter, and 60 percent with friends or family. Besides lodging, additional costs could include traffic congestion, food, or entertainment (Whitehead 2003). Our estimates should therefore be considered conservative. Empirical exploration of these expenditures is an area for future research.

Finally, as discussed throughout the paper, we do not speak to the optimality of any particular hurricane evacuation. At the optimum, an emergency manager must weigh the expected avoided mortality costs from an evacuation against the costs. This optimization requires an explicit consideration of the consequences of type I and type II errors. The estimates of this paper are informative for this decision-making process. Still, future research in this area will be increasingly important as large natural disasters expand the need for evacuation.

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Appendix to "The Cost of Hurricane Evacuations"

Jacob Gellman, Hannah Hennighausen, Brett Watson, Kevin Berry

29 October 2024

Appendix A: Additional figures A2

Appendix B: Insights from changes in foot traffic A3

Appendix C: Insights from changes in outmigration A8

Appendix A: Additional figures

Figure A1: Example raw data for hurricane path

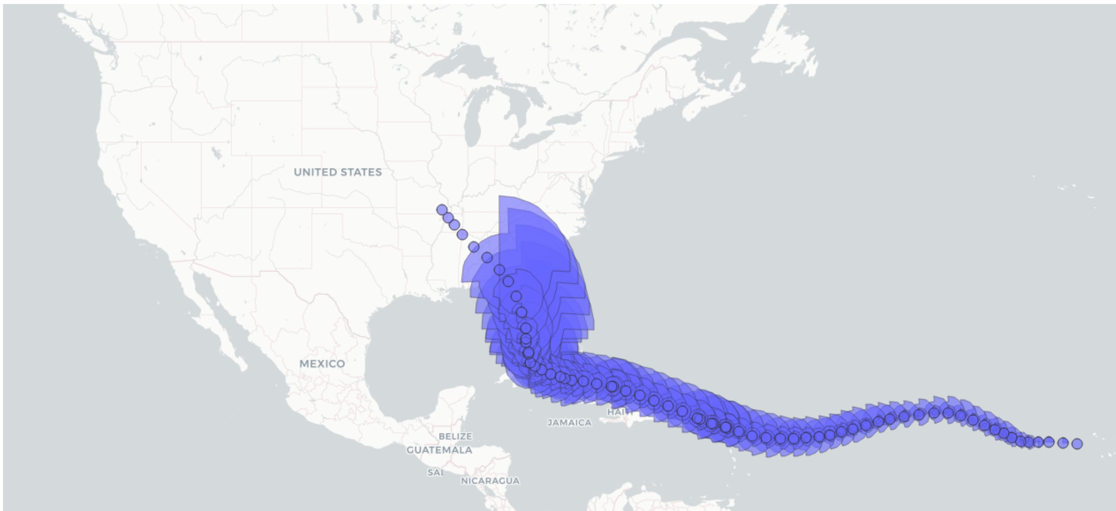
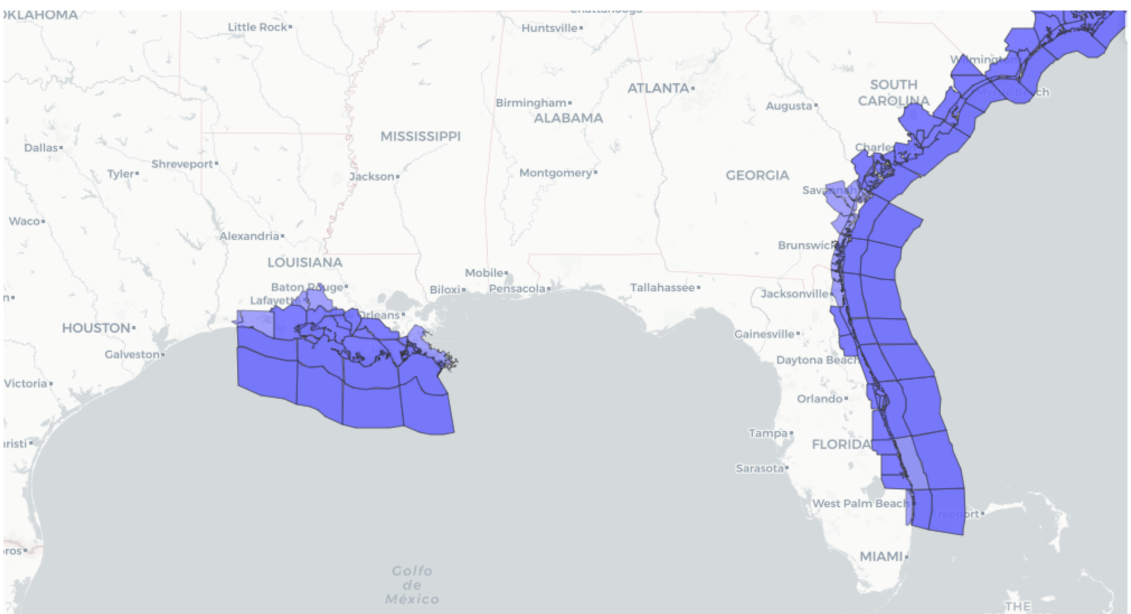


Figure A2: Example raw data for NWS hurricane alerts during 2019



Appendix B: Insights from changes in foot traffic

B.1 Physical mechanisms for avoidance

Table B1: Foot traffic, heterogeneity by wind speed

	(1)	(2)
Hurricane path	-0.0273*	-0.0273*
	(0.0153)	(0.0153)
Disaster decl.	0.0466***	0.0463***
	(0.0097)	(0.0098)
Hurricane path × Disaster decl.	-0.0765***	
	(0.0194)	
Hurricane path × Disaster decl. × Wind spd 40-70		-0.0698***
		(0.0216)
Hurricane path × Disaster decl. × Wind spd 71-90		-0.0904***
		(0.0203)
Hurricane path × Disaster decl. × Wind spd 91-110		-0.0279
		(0.0374)
Hurricane path × Disaster decl. × Wind spd 111-130		-0.0935***
		(0.0290)
Hurricane path × Disaster decl. × Wind spd 131-162		-0.1779***
		(0.0398)
Block group FE	Yes	Yes
Month-year FE	Yes	Yes
Observations	3,658,837	3,658,837

Notes: Wind speed is reported in miles per hour. A block group is considered in the path of a storm if it saw sustained winds greater than 39 mph. Disaster declarations are measured at a county level. Standard errors are clustered by county. Weights are by block group population. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B2: Foot traffic, heterogeneity by flooding

	(1)	(2)	(3)
Hurricane path	-0.0273*	-0.0269*	
	(0.0153)	(0.0152)	
Disaster decl.	0.0466***	0.0475***	
	(0.0097)	(0.0096)	
Hurricane path × Disaster decl.	-0.0765***	-0.0755***	
	(0.0194)	(0.0193)	
Flood		-0.0150**	
		(0.0061)	
Hurricane path × Flood = 0			-0.0262*
			(0.0151)
Hurricane path × Flood = 1			-0.0564**
			(0.0226)
Disaster decl. × Flood = 0			0.0496***
			(0.0103)
Disaster decl. × Flood = 1			0.0086
			(0.0179)
Hurricane path × Disaster decl. × Flood = 0			-0.0792***
			(0.0204)
Hurricane path × Disaster decl. × Flood = 1			-0.0163
			(0.0338)
Block group FE	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes
Observations	3,658,837	3,658,837	3,658,837

Notes: Flooding is measured as a binary variable if a block group had any NFIP claims in the month. A block group is considered in the path of a storm if it saw sustained winds greater than 39 mph. Disaster declarations are measured at a county level. Standard errors are clustered by county. Weights are by block group population. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B.2 Demographic heterogeneity of avoidance

Table B3: Foot traffic, demographic heterogeneity

	(1)	% Black (2)	% Hispanic (3)	% White (4)	% Bachelor Deg. (5)	Med. Inc. (6)
Hurricane path	-0.0273*	-0.0273*	-0.0273*	-0.0273*	-0.0274*	-0.0275*
	(0.0153)	(0.0153)	(0.0153)	(0.0153)	(0.0153)	(0.0151)
Disaster decl.	0.0466***	0.0466***	0.0465***	0.0465***	0.0464***	0.0460***
	(0.0097)	(0.0097)	(0.0097)	(0.0097)	(0.0097)	(0.0097)
Hurricane path × Disaster decl.	-0.0765***					
	(0.0194)					
Hurricane path × Disaster decl. × Het. Lowest Q		-0.1228***	-0.0568***	-0.0729***	-0.0526***	-0.0649***
		(0.0282)	(0.0197)	(0.0206)	(0.0190)	(0.0202)
Hurricane path × Disaster decl. × Het. 2Q		-0.0747***	-0.0877***	-0.0558***	-0.0596***	-0.0674***
		(0.0192)	(0.0207)	(0.0175)	(0.0197)	(0.0188)
Hurricane path × Disaster decl. × Het. 3Q		-0.0549***	-0.0892***	-0.0647***	-0.0738***	-0.0765***
		(0.0185)	(0.0185)	(0.0192)	(0.0210)	(0.0195)
Hurricane path × Disaster decl. × Het. Highest Q		-0.0686***	-0.0612***	-0.1132***	-0.1148***	-0.0890***
		(0.0207)	(0.0226)	(0.0274)	(0.0205)	(0.0204)
Block group FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,658,837	3,658,837	3,658,837	3,658,837	3,658,261	3,526,916

Notes: Demographic heterogeneity is measured by quartile. A block group is considered in the path of a storm if it saw sustained winds greater than 39 mph. Disaster declarations are measured at a county level. Standard errors are clustered by county. Weights are by block group population. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table B4: Foot traffic, heterogeneity by urban development

	(1)	% Car Alone (2)	% Homeowner (3)	% Sing. Fam. Homes (4)	% Mobile Homes (5)	Home Val. (6)	Urban (7)
Hurricane path	-0.0273*	-0.0273*	-0.0277*	-0.0273*	-0.0273*	-0.0277*	-0.0273*
	(0.0153)	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0150)	(0.0153)
Disaster decl.	0.0466***	0.0466***	0.0462***	0.0463***	0.0463***	0.0464***	0.0465***
	(0.0097)	(0.0097)	(0.0097)	(0.0097)	(0.0097)	(0.0098)	(0.0097)
Hurricane path × Disaster decl.	-0.0765***						
	(0.0194)						
Hurricane path × Disaster decl. × Het. Lowest Q		-0.1069***	-0.0753***	-0.1181***	-0.1132***	-0.0648***	-0.0208
		(0.0201)	(0.0206)	(0.0234)	(0.0266)	(0.0185)	(0.0181)
Hurricane path × Disaster decl. × Het. 2Q		-0.0775***	-0.0714***	-0.0623***	-0.0912***	-0.0547***	-0.0298
		(0.0204)	(0.0189)	(0.0183)	(0.0227)	(0.0177)	(0.0193)
Hurricane path × Disaster decl. × Het. 3Q		-0.0717***	-0.0669***	-0.0491***	-0.0591***	-0.0595***	-0.0318*
		(0.0202)	(0.0191)	(0.0188)	(0.0187)	(0.0198)	(0.0167)
Hurricane path × Disaster decl. × Het. Highest Q		-0.0533***	-0.0882***	-0.0635***	-0.0465***	-0.1135***	-0.0930***
		(0.0193)	(0.0215)	(0.0218)	(0.0171)	(0.0235)	(0.0214)
Block group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,658,837	3,655,180	3,650,081	3,655,261	3,655,261	3,413,925	3,658,837

Notes: Demographic and community characteristic heterogeneity are measured by quartile. A block group is considered in the path of a storm if it saw sustained winds greater than 39 mph. Disaster declarations are measured at a county level. Standard errors are clustered by county. Weights are by block group population. * p < 0.1, ** p < 0.05, *** p < 0.01.

B.3 Informational mechanisms for avoidance

Table B5: Foot traffic, heterogeneity by hurricane category

	(1)	(2)
Hurricane path	-0.0273*	-0.0271*
	(0.0153)	(0.0152)
Disaster decl.	0.0466***	0.0459***
	(0.0097)	(0.0098)
Hurricane path × Disaster decl.	-0.0765***	
	(0.0194)	
Hurricane path × Disaster decl. × Cat. 0		0.0223
		(0.0263)
Hurricane path × Disaster decl. × Cat. 1		-0.0965***
		(0.0233)
Hurricane path × Disaster decl. × Cat. 2		-0.0004
		(0.0253)
Hurricane path × Disaster decl. × Cat. 3		-0.0750***
		(0.0238)
Hurricane path × Disaster decl. × Cat. 4		-0.0918***
		(0.0236)
Hurricane path × Disaster decl. × Cat. 5		-0.1776***
		(0.0467)
Block group FE	Yes	Yes
Month-year FE	Yes	Yes
Observations	3,658,837	3,658,837

Notes: Category measures a storm's Saffir-Simpson category. A block group is considered in the path of a storm if it saw sustained winds greater than 39 mph. Disaster declarations are measured at a county level. Standard errors are clustered by county. Weights are by block group population. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B6: Foot traffic, heterogeneity by NWS alerts

	(1)	(2)	(3)
Hurricane path	-0.0273*	-0.0246	
	(0.0153)	(0.0152)	
Disaster decl.	0.0466***	0.0480***	
	(0.0097)	(0.0094)	
Hurricane path × Disaster decl.	-0.0765***	-0.0682***	
	(0.0194)	(0.0204)	
NWS alert		-0.0244**	
		(0.0100)	
Hurricane path × NWS alert = 0			-0.0237
			(0.0148)
Hurricane path × NWS alert = 1			-0.0548**
			(0.0265)
Disaster decl. × NWS alert = 0			0.0504***
			(0.0099)
Disaster decl. × NWS alert = 1			-0.0019
			(0.0299)
Hurricane path × Disaster decl. × NWS alert = 0			-0.0757***
			(0.0203)
Hurricane path × Disaster decl. × NWS alert = 1			-0.0084
			(0.0396)
Block group FE	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes
Observations	3,658,837	3,658,837	3,658,837

Notes: NWS alerts are watches, advisories, and warnings reported for each block group by month. A block group is considered in the path of a storm if it saw sustained winds greater than 39 mph. Disaster declarations are measured at a county level. Standard errors are clustered by county. Weights are by block group population. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix C: Insights from changes in evacuation

C.1 Physical mechanisms of evacuation

Table C1: Marginal utility in evacuation, heterogeneity by wind speed

	(1)	(2)
Travel cost (dollars)	-0.0062***	-0.0062***
	(0.0001)	(0.0001)
Hurricane (orig.)	0.0424**	
	(0.0213)	
Hurricane (dest.)	-0.0138	-0.0138
	(0.0090)	(0.0089)
Hurricane (orig.) × Hurricane (dest.)	0.0056	0.0049
	(0.0293)	(0.0292)
Hurricane (orig.) × Wind spd 40-70		0.0401*
		(0.0232)
Hurricane (orig.) × Wind spd 71-90		0.0311
		(0.0207)
Hurricane (orig.) × Wind spd 91-110		0.0615
		(0.0529)
Hurricane (orig.) × Wind spd 111-130		0.0826**
		(0.0327)
Hurricane (orig.) × Wind spd 131-162		0.1525***
		(0.0333)
Block group orig. FE	Yes	Yes
County dest. FE	Yes	Yes
Month-year FE	Yes	Yes
Observations	43,908,471	43,908,471

Notes: Wind speed is reported in miles per hour. An origin block group is considered hurricane-affected if it saw sustained winds greater than 39 mph and received a disaster declaration. A destination county is considered hurricane-affected if it received a disaster declaration. Standard errors are clustered by origin county. Weights are by origin block group population. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C.2 Informational mechanisms of evacuation

Table C2: Marginal utility in evacuation, heterogeneity by hurricane category

	(1)	(2)
Travel cost (dollars)	-0.0062***	-0.0062***
	(0.0001)	(0.0001)
Hurricane (orig.)	0.0424**	
	(0.0213)	
Hurricane (dest.)	-0.0138	-0.0140
	(0.0090)	(0.0090)
Hurricane (orig.) × Hurricane (dest.)	0.0056	0.0016
	(0.0293)	(0.0299)
Hurricane (orig.) × Cat. 0		-0.0228
		(0.0237)
Hurricane (orig.) × Cat. 1		0.0745***
		(0.0169)
Hurricane (orig.) × Cat. 2		0.0317
		(0.0357)
Hurricane (orig.) × Cat. 3		0.0275
		(0.0327)
Hurricane (orig.) × Cat. 4		0.0538**
		(0.0271)
Hurricane (orig.) × Cat. 5		0.0542*
		(0.0301)
Block group orig. FE	Yes	Yes
County dest. FE	Yes	Yes
Month-year FE	Yes	Yes
Observations	43,908,471	43,908,471

Notes: Category measures a storm's Saffir-Simpson category. An origin block group is considered hurricane-affected if it saw sustained winds greater than 39 mph and received a disaster declaration. A destination county is considered hurricane-affected if it received a disaster declaration. Standard errors are clustered by origin county. Weights are by origin block group population. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C3: Marginal utility in evacuation, heterogeneity by NWS alert

	(1)	(3)	(2)
Travel cost (dollars)	-0.0062***	-0.0062***	-0.0062***
	(0.0001)	(0.0001)	(0.0001)
Hurricane (orig.)	0.0424**	0.0501**	0.0501**
	(0.0213)	(0.0248)	(0.0249)
Hurricane (dest.)	-0.0138	-0.0138	-0.0139
	(0.0090)	(0.0090)	(0.0090)
Hurricane (orig.) × Hurricane (dest.)	0.0056	0.0061	0.0062
	(0.0293)	(0.0293)	(0.0293)
NWS alert		-0.0024	
		(0.0183)	
Hurricane (orig.) × NWS alert		-0.0129	-0.0153
		(0.0249)	(0.0186)
Block group orig. FE	Yes	Yes	Yes
County dest. FE	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes
Observations	43,908,471	43,908,471	43,908,471

Notes: NWS alerts are watches, advisories, and warnings reported for each block group by month. An origin block group is considered hurricane-affected if it saw sustained winds greater than 39 mph and received a disaster declaration. A destination county is considered hurricane-affected if it received a disaster declaration. Standard errors are clustered by origin county. Weights are by origin block group population. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.