The Cost of Hurricane Evacuations

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Abstract

Climate-driven tropical storms pose physical risks for public safety. Evacuation is a key protective action against hurricanes, but it may be costly for individuals. Despite their importance to emergency management decisions, there is little evidence on the size of these costs. In this paper we estimate the welfare cost of hurricane evacuations and sheltering. We combine spatial data on hurricanes and evacuation orders with billions of records of individuals' cell phone-derived movement activity. 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 and sheltering can be large when compared to mortality costs, averaging 55 percent as a share of the value of statistical life lost. Our results demonstrate a novel application of the travel cost demand method and document an understudied cost of hurricanes.

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1 Introduction

Hurricanes caused more than $340 billion in direct damages in the United States between 2018 and 2024 (NOAA NCEI 2024). In addition to these property losses, tropical storms pose substantial physical risks to individuals. Mortality can account for a high share of overall hurricane damages, with the value of statistical life lost (VSL) frequently exceeding 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 evacuation. Understanding the costs and benefits of evacuation is crucial for public policy, as the direct expenditures of evacuation can be costly (Whitehead 2003). 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 estimate the welfare costs of hurricane evacuations and sheltering. We combine spatial data on hurricanes and evacuation orders with billions 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 evacuation and sheltering.

Our analysis proceeds in several steps. We first present reduced form evidence on the rate of evacuation and sheltering during a tropical storm. Outmigration rises substantially for more severe hurricanes and when individuals are subject to mandatory evacuation orders. For Category 4 and 5 wind speeds, the share of individuals leaving their home county rises by 59 percent when subject to a mandatory evacuation order, and they travel substantially larger distances at the tail end of the distribution. On the other hand, at low to moderate wind speeds, individuals have limited or no compliance with voluntary evacuation orders, electing instead to shelter. Descriptively, outmigration is strongest for higher education, higher income, and urban areas. Notably, at low to moderate wind speeds, no demographic group responds to voluntary evacuation orders. Taken together, these analyses build confidence in the use of cell phone-derived mobility data to measure the effects of hurricanes on movement patterns.

To frame the welfare implications, we use graphical evidence to illustrate how hurricanes could either induce sheltering or evacuation costs, depending on the severity of a storm. These costs are driven by individual movement decisions, which we structurally model with a discrete choice travel cost demand framework. 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. In contrast to previous travel cost applications, the choice set includes any generalized location, rather than limited specific sites of interest. 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 274 million observations of origin-destination movement flows.

The estimation generates several insights. At high wind speeds and when subject to evacuation orders, individuals show strongly positive willingness to pay (WTP) to evacuate from hurricane-affected locations. Under Category 4 and 5 wind speeds, welfare costs are approximately $343 per person when subject to a mandatory evacuation order. Conversely, at low to moderate wind speeds, individuals' WTP takes the opposite sign, demonstrating sheltering costs that range from $14 to $24 per person. While smaller on a per-person basis, in the aggregate the total cost of sheltering dominates the cost of evacuation due to the higher prevalence of low-intensity events.

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. Evacuation costs range from $11 million to $133 million for Category 3 and greater hurricanes. These costs are generally increasing for higher category storms, which tend to have a greater number of evacuation orders. Over the study period, total evacuation costs amount to nearly half a billion dollars, while sheltering costs total $1.8 billion. To contextualize the estimates, we compare them to the property damages and mortality costs of hurricanes. For most storms, evacuation and sheltering costs are small when compared to total property damage. More germane to emergency management is the comparison to mortality costs. We find that the costs of evacuation and sheltering can be large when compared to mortality costs, averaging a ratio of 55 to 100 but occasionally exceeding total VSL, particularly for less-damaging storms. 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 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;

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

Lee and Beatty 2024; Rubin and Holloway 2026) and in descriptive case studies of single hurricanes (Li, Qiang, and Cervone 2024; Yabe 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; Hochard, Li, and Abashidze 2022; Molina and Rudik 2026).

Lastly, we demonstrate a novel application of the travel cost demand method. A recent literature has focused on valuation of environmental costs using large, administrative datasets (Earle and Kim 2026; Gellman, Walls, and Wibbenmeyer 2025). Interest is growing in the use of large datasets to estimate structural utility parameters; however, doing so can present computational challenges (Earle 2025). Some researchers have therefore developed methods which recover individual-level parameters using aggregated data (Melstrom and Reeling 2024). Among these are studies that aggregate visitors to recreation sites using a market shares approach from Berry, Levinsohn, and Pakes (1995), for example Cheng and Wan (2026) and Connolly et al. (2026). We follow this line of research, but invert the framework. While travel cost demand models traditionally focus on visitors to a specified set of sites, we estimate utility parameters using individuals' generalized movement to any location. Our methods could be applied to settings valuing other environmental amenities or disamenities, for example temperature gradients or acute pollution events.

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 evacuation and sheltering during a hurricane. Section 4 develops a structural model of hurricane evacuation and reports empirical estimates of welfare costs. In Section 5 we apply these estimates to back-of-the-envelope calculations of the total cost of hurricane evacuations and sheltering by storm. Section 6 concludes.

2 Data

We combine data on hurricanes and tropical storms, government alerts, and cell phone-derived movement patterns to create two estimating datasets. The first dataset is a panel at the Census block group by week level over the years 2019 to 2023. These data provide reduced form evidence on evacuation, sheltering, and foot traffic during a tropical storm or 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 week for the years 2019 to 2023. These paired movement flows are used to structurally estimate welfare costs in a travel cost demand framework.

2.1 Cell phone mobility data

To understand mobility patterns during hurricanes, we draw from two databases of cell phone-based geolocation. The main data provider for the analysis is Cuebiq, formerly known as Spectus, which has been used in travel cost demand applications by Ahmadiani and Woodward (2026), Cheng and Wan (2026), and Connolly et al. (2026), among others.[2] We additionally source data from Advan, data which were formerly managed by SafeGraph.[3] These data have been used to measure mobility responses to environmental hazards such as wildfire smoke (Burke et al. 2022; Rubin and Holloway 2026). Both Cuebiq and Advan data have been found to be demographically and spatially representative of the US population (Hsu et al. 2024; Kang et al. 2020; Squire 2019).[4]

For both providers, movement data are collected from smartphone apps using location-based services. The Cuebiq data record anonymous device pings continuously throughout space. The minimum unit of observation is a unique device by day, where each row reports the device's home Census block group along with a list of counties it visited. For the study area and time period, there are more than 2.48 billion device by day observations. Following Rubin and Holloway (2026), we aggregate each device's visit activity to a weekly level to smooth short-term intertemporal substitutions of travel. In addition, based on past survey evidence, we restrict the choice set of destination counties to be within a 500 mile driving distance of an origin block group to preclude the possibility of air travel, which can complicate the calculation of travel cost (English et al. 2018). Because we are interested in an individual's discrete choice, we frame a device's uniquely chosen alternative as its farthest

2. Cuebiq. 2026. "Data Platform." https://cuebiq.com/platform.

3. Advan Research. 2025. "Foot Traffic / Neighborhood Patterns." Dewey Data. https://doi.org/10.82551/MS2A-2E59.

4. In Appendix B we report summary statistics on sample representativeness.

observed destination in a given week, which eliminates chained trips and double counting. We aggregate the data to record the number of visitors flowing from an origin block group to a destination county in a given week. For the reduced form analysis we also summarize these data at a simpler block group by week level, using several measures of outmigration as definitions of evacuation.

As supplementary evidence, we draw on Advan's Neighborhood Patterns dataset, which records the daily number of visits ("foot traffic") in a Census block group at a daily level. These visits differ from Cuebiq's in that they rely on a device stopping at a "Point of Interest" (POI), which can represent any identifiable commercial, industrial, or other location.[5] While the Cuebiq device data represent an extensive margin choice, the Advan foot traffic data are an intensive margin measure of the total activity level in a location. Importantly, this foot traffic could be generated either by residents within the block group or from outside it.

We limit attention to the eight coastal Southeast states spanning from Texas to North Carolina. For tractability, we focus on origin block groups from counties within 100 miles of the coast, a threshold used by Beatty, Shimshack, and Volpe (2019) to define hurricane-affected locations. Lastly, we restrict the data to the months of June through November, which is hurricane season, over the years 2019 to 2023. The reduced form analysis of Section 3 measures evacuation at a block group by week level, with a panel of approximately 3.2 million observations. The structural analysis of Section 4 measures movement from origin block groups to destination counties, resulting in approximately 274 million paired observations. This panel includes rejected choice alternatives, i.e. pairs with zero visit counts.

2.2 Hurricane and tropical storm exposure

To measure the location and timing of tropical storms and 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 storm, as well as wind speed radii associated with 34-, 50-, and 64-knot winds. They also contain information on intensity, which measures peak

5. 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.

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

wind speed during the interval, and the Saffir-Simpson scale hurricane category (Tropical Storm and Category 1 through 5). Figure A1 in Appendix A 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 week.[7]

Additionally, we use information from NOAA NCEI, which reports total property damages and deaths attributable to a storm.[8] 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 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.[9] We identify block groups that received a NWS alert by overlaying polygon shapefiles of temporally-explicit watches and warnings 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 large differences in weather due to topography or proximity to water. Figure A2 in Appendix A displays an example of the raw data for 2019. Visually, zones are smaller when near to the coast.

7. Maximum wind speed has been used as a measure of treatment intensity by, for example, Molina and Rudik (2026) and Young and Hsiang (2024).

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

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

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.[10] These terms carry different legal implications that may affect a resident's decision to evacuate.[11] 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 government 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. While entire counties may be subject to an evacuation order, most states and counties issue targeted orders for predefined evacuation zones.[12] We obtain shapefiles for every state's evacuation zones and spatially match them to orders that use these designations. Alternatively, some evacuation orders apply only to specific cities or neighborhoods. We manually compile shapefiles from OpenStreetMap for these cases, which avoids coding an entire county as treated.[13]

In total, we compile information for 358 unique evacuation orders for the study period. Since many areas receive both voluntary and mandatory orders, i.e. when a voluntary order is

10. 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: US Department of Homeland Security. 2025. "Federal Evacuation Support Annex to the Response and Recovery Federal Interagency Operational Plans." https://www.fema.gov/sites/default/files/documents/fema_rd_federal-evacuation-support-annex_042025.pdf.

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

12. For instance: South Carolina Emergency Management Division. 2026. "Know Your Zone." https://scemd.org/prepare/know-your-zone.

13. For example, four evacuated towns during Hurricane Florence were Emerald Isle, Indian Beach, Pine Knoll Shores, and Atlantic Beach in Carteret County, North Carolina. Shapefiles for these towns or neighborhoods are available with unique identifiers from OpenStreetMap, and can be scraped with packages such as osmdata in the R programming language. See: OpenStreetMap. 2026. "Relation: Emerald Isle (177438)." https://www.openstreetmap.org/relation/177438.

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. In almost all cases, evacuation orders are declared on either the same day or one day ahead of the effective date.

2.4 Demographics

To explore demographic moderators, we match Census Bureau data at a block group level.[14] Relevant variables include race, education, income, and urban population. The cell phone mobility data define block groups based on 2010 Census geographies, which were effective during the years 2010 through 2019. Where available, we use American Community Survey data for the year 2018.[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. As discussed in Section 2.1, we restrict attention to driving distances within 500 miles, based on past survey evidence of travel behavior (English et al. 2018). These restrictions result in 4.2 million unique routes.

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

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

for travel distance D_{zj} and travel time T_{zj}. The variable p_{zt}^D captures the per-mile travel

14. United States Census Bureau. 2026. https://data.census.gov.

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. This specification follows Rubin and Holloway (2026).

16. OSRM. 2025. "osrm: Interface Between R and the OpenStreetMap-Based Routing Service OSRM." https://cran.r-project.org/web/packages/osrm/index.html.

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_{zt}^{T} as one-half the average household income in the block group's ZIP code tabulation area divided by 2,080 working hours per year (English et al. 2018). In Appendix A, we show sensitivity to using either one-third or two-thirds of the wage rate as the value of travel time, following recommendations by Lupi, Phaneuf, and von Haefen (2020). 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. Figure 1 provides a visualization of the frequency of treatment over the study period of 2019 to 2023. Panel (a) shows the number of times that an area experienced a tropical storm of any category. For most areas in the Southeast it is common to have experienced a tropical storm. However, only some coastal areas experienced a Category 3 or greater hurricane over the study period, as shown in panel (b). Panel (c) displays the frequency of mandatory evacuation orders, which visually overlaps with the Category 3 areas of panel (b). The empirical analysis considers these varying measures of treatment both jointly and separately.

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.

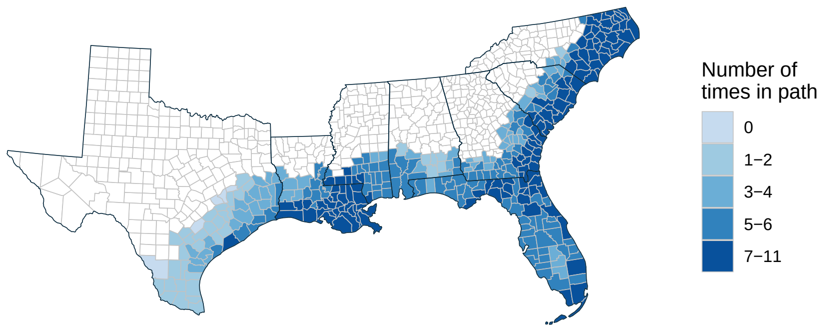
18. Bureau of Transportation Statistics. 2024. "Average Fuel Efficiency of US Light Duty Vehicles." https://www.bts.gov/content/average-fuel-efficiency-us-light-duty-vehicles.

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.

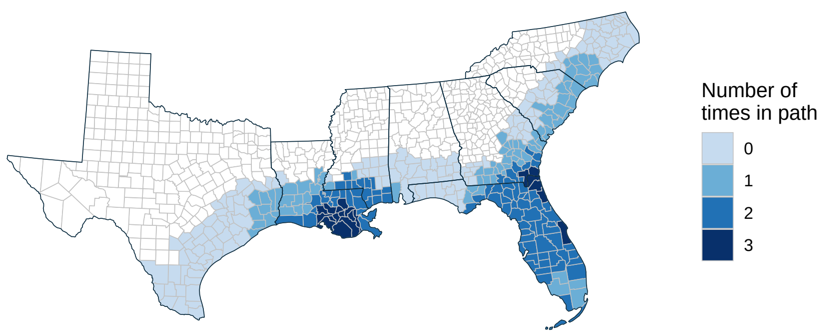
20. Marginal depreciation cost is computed as the difference between "reduced depreciation" and "increased depreciation" between 10,000 and 20,000 miles, divided by 10,000 miles, as in English et al. (2018).

Figure 1: Treatment frequency over 2019 to 2023

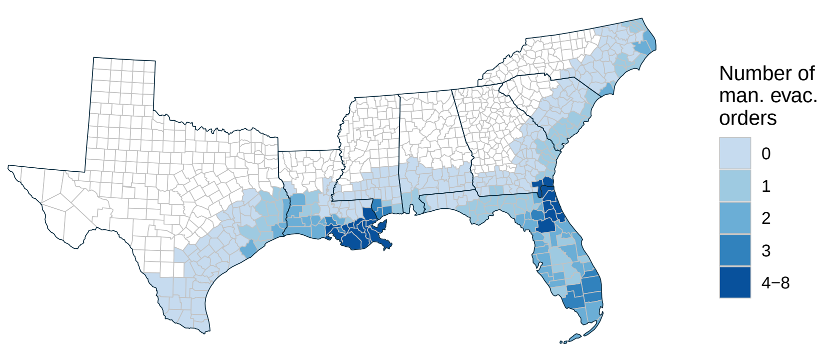
(a) Tropical storm path, any category



(b) Hurricane path, Category 3 or greater



(c) Mandatory evacuation orders



Notes: Panel (a) maps the frequency that an area fell in the path of a tropical storm of any category over the study period of 2019 to 2023. Panel (b) maps the number of times an area experienced a Category 3 or greater hurricane during this time. Categories are coded according to the wind speed at the time a storm intersected a block group. Panel (c) plots the frequency of mandatory evacuation orders.

Table 1 summarizes variation in the data by individual storm. We observe fourteen named hurricanes of Category 1 or greater and seventeen tropical storms. As in Figure 1, the reported category reflects the maximum wind speed we observe at the time of intersection with a block group; for example, although Hurricane Dorian reached Category 5 over the Bahamas, by the time it touched the US Southeast it had weakened to a Category 4 storm. For each storm, the table reports the number of block group by week observations that experienced evacuation orders or were ever in the path of the storm. Over 2019 to 2023, the resulting dataset contains 25,498 unique block groups, 342 unique counties, and approximately 3.2 million block group by week observations, with more than 122,000 observations that fell in the path of a tropical storm or hurricane.

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

Storm	Cat.	Year	Obs w/ Vol. Evac	Obs w/ Man. Evac	Obs In Path
Ian	5	2022	1,282	2,588	14,013
Dorian	4	2019	1,310	2,688	5,395
Ida	4	2021	880	717	3,164
Idalia	4	2023	852	2,100	9,042
Laura	4	2020	1,524	960	1,869
Delta	3	2020	306	534	3,336
Zeta	3	2020	335	173	4,654
Sally	2	2020	545	354	1,685
Barry	1	2019	589	275	2,967
Elsa	1	2021	231	0	6,615
Hanna	1	2020	62	0	1,001
Isaias	1	2020	1,206	22	5,457
Nicholas	1	2021	17	15	3,710
Nicole	1	2022	947	1,330	12,701
Other tropical storms (N=17)	0		20	71	46,575
Treated					122,184
Untreated					3,038,777
Total					3,160,961

Notes: Observations represent block groups by week. Category reports the maximum Saffir-Simpson category achieved by a storm when intersecting a block group in the sample. 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. A block group is considered in the path of a tropical storm if it saw sustained winds greater than 39 miles per hour.

3 Reduced Form Evidence

Before proceeding to the structural estimation, we first examine reduced form evidence on evacuation, sheltering, and foot traffic during a hurricane. These analyses shed light on behavioral responses to tropical storms and government alerts across varying levels of treatment intensity. 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

We adopt two measures of evacuation from Rubin and Holloway (2026), who studied wildfire smoke avoidance using mobile device data. First, they calculated the share of an origin block group's visits that occurred outside of the home county. Second, they recorded the 75th percentile of distances traveled by a block group's devices, which captures how the right tail of the distribution in travel distances responds to an environmental hazard. Analogously, we calculate the share of devices s^0_{zt} staying in their home county for every block group z in week and year t. We also compute the 75th percentile of distance traveled by a block group's devices, $dist^{75}_{zt}$. We expect to observe sheltering for mild storms and outmigration for severe hurricanes.

As a third dependent variable, we estimate changes in total foot traffic during a hurricane, $\log(visits_{zt})$. This variable measures the total number of stops in a block group and provides an intensive margin measure of activity for a given area. Importantly, foot traffic is created both by a block group's own residents and by non-residents traveling to it. It is therefore reasonable to expect that this estimation produces spillovers; individuals in affected areas will substitute activity to 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 a covariate for unaffected block groups' inverse distance to a hurricane storm radius.

Let h_{zt} be an indicator variable equal to one if block group z fell in the path of a tropical storm or hurricane in week and year t. Define a binned tropical storm wind speed variable

$H^b_{zt} \equiv h_{zt} \cdot \mathbb{1}\{wind_{zt} \in b\}$ for bins $b \in B$. We estimate:

$$y_{zt} = \sum_{b \in B} H^b_{zt}(\phi_b + \phi_b^{Vol} O^{Vol}_{zt} + \phi_b^{Man} O^{Man}_{zt}) + \delta_z + \lambda_t + \eta_{zt}, \quad (2)$$

where $y_{zt} \in \{s^0_{zt},\ dist^{75}_{zt}\}$, and O^{Vol}_{zt} and O^{Man}_{zt} are indicators for voluntary or mandatory evacuation orders. Block group fixed effects δ_z account for location-specific, time-invariant unobservables, while week 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 the county level.

The parameters of interest are ϕ_b, $(\phi_b + \phi_b^{Vol})$, and $(\phi_b + \phi_b^{Man})$, for each wind speed bin b. These parameters measure changes in y_{zt} relative to the omitted category of no tropical storm force wind. The identification assumption is: $\mathbb{E}[\ \eta_{zt} \mid \{H^b_{zt}\}_{b \in B},\ O^{Vol}_{zt},\ O^{Man}_{zt},\ \delta_z,\ \lambda_t\ ] = 0$. Identification requires that the effect of hurricanes and evacuation orders be exogenous conditional on fixed effects that control for average traits of individuals by block group and time-varying factors common to all groups. Conditional on these fixed effects, which capture unobservables such as sorting by preferences or beliefs, the effects of hurricanes and government alerts are treated as exogenous from the perspective of the individual.[21]

For regressions with $\log(visits_{zt})$ as the dependent variable, we additionally include a covariate $(1 - h_{zt})d^{-1}_{zt}$, which measures the inverse distance to a tropical storm radius for block groups outside of the storm path. This variable is intended to capture spillovers in foot traffic. We estimate:

$$y_{zt} = \sum_{b \in B} \vartheta_b H^b_{zt} + \theta(1 - h_{zt})d^{-1}_{zt} + \delta_z + \lambda_t + \upsilon_{zt}, \quad (3)$$

where $y_{zt} = \log(visits_{zt})$. The parameters of interest are the coefficients $\{\vartheta_b\}_{b \in B}$. The identification assumption is similar to that of the evacuation regressions in Equation 2, but additionally requires that the inverse distance term adequately capture spillovers. Even without this assumption, the inclusion of many control units, with more than 3 million untreated observations (see Table 1), implies that potential SUTVA violations would likely

21. See, for example, Bakkensen and Barrage (2022) for a discussion of the effect of flood risk beliefs on sorting.

have a negligible effect on the coefficients $\{\vartheta_b\}_{b \in B}$ since they represent a small share of the untreated observations.

3.2 Evacuation, sheltering, and foot traffic during a hurricane

Figure 2 plots results from estimation of Equations 2 and 3. Wind speed bins are informed by the Saffir-Simpson hurricane wind scale, where the 40 to 70 mile per hour bin is a tropical storm, the middle three bins are approximately Categories 1 through 3 winds, and the top bin captures Category 4 and 5 winds. We plot the total effect under each evacuation scenario, i.e. ϕ_b, $(\phi_b + \phi_b^{Vol})$, and $(\phi_b + \phi_b^{Man})$, with standard errors computed using the delta method. To test whether upstream information channels are transmitted downstream, we also separately estimate Equation 2 using NWS alerts rather than evacuation orders.

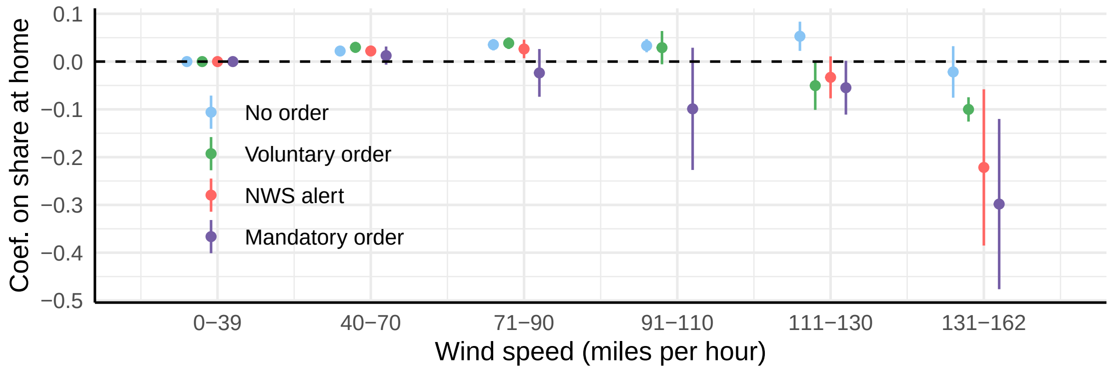
The reduced form exercise reveals several patterns. First, outmigration rises at higher wind speeds and when block groups are subject to mandatory evacuation orders. At Category 4 and 5 winds and under mandatory evacuation orders, the share of individuals staying in their home area drops by 0.30, which is approximately 59 percent relative to the mean of 0.51. The 75th percentile of distance traveled also rises by more than 220 miles under Category 4 to 5 winds, which is nearly an order of magnitude larger than the dependent variable mean of 47.2 miles.

Second, sheltering rises at milder wind speeds and when individuals are not subject to evacuation orders. For mild wind speeds, the share staying home rises by up to 0.05, or 10 percent of the mean of the dependent variable s^0_{zt}. Notably, at lower wind speeds, individuals appear not to substantially alter behavior under voluntary evacuation orders, despite being warned to leave. The response disparity between mandatory and voluntary orders is consistent with past survey literature and case studies (Thompson, Garfin, and Silver 2017; Younes, Darzi, and Zhang 2021).

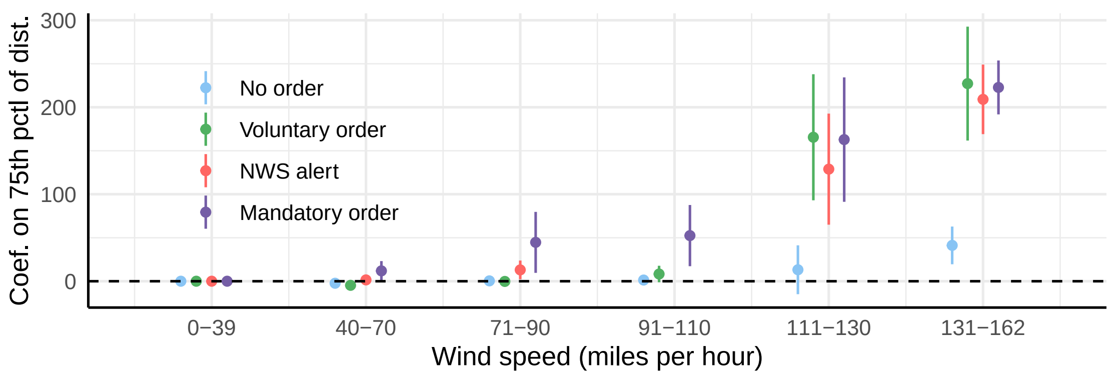
A third pattern is that the effects of NWS alerts resemble the estimates for evacuation orders. Under the Protective Action Decision Model used by emergency management researchers, this result would suggest that upstream NWS information is transmitted downstream to local emergency managers. It also serves as a robustness check on evacuation orders by providing an alternative measure of government information provision.

Figure 2: Reduced form coefficient plots for evacuation, sheltering, and foot traffic

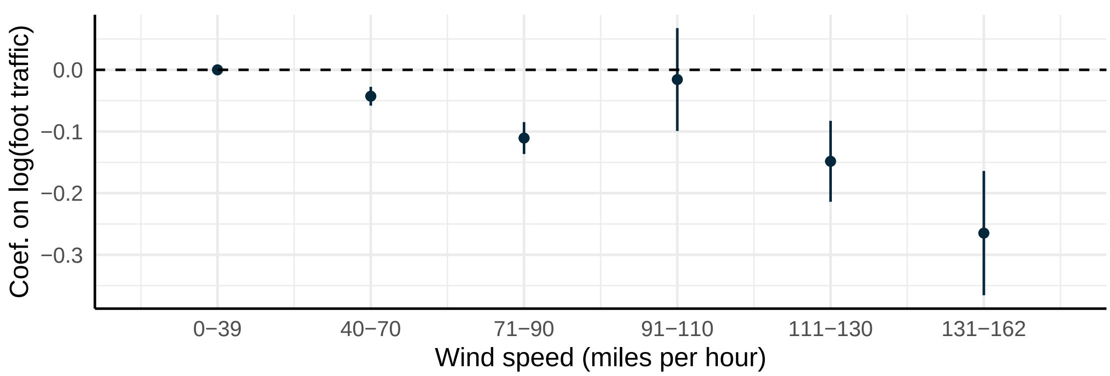
(a) Share staying in home area



(b) The 75th percentile of distance traveled



(c) Foot traffic



Notes: Panels (a) and (b) plot total effects from estimating Equation 2, i.e. ϕ_b, $(\phi_b + \phi_b^{Vol})$, and $(\phi_b + \phi_b^{Man})$, across wind speed bins. 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. Panel (c) displays coefficients from estimating Equation 3. The mean of the dependent variables are 0.51 for the share staying home s^0_{zt}, 47.2 miles for the 75th percentile of distance traveled $dist^{75}_{zt}$, and 5,553.4 visits for foot traffic $visits_{zt}$. Table A1 in Appendix A reports full regression results. Standard errors for the combined effects are computed using the delta method. N = 3,157,580.

Lastly, total activity in hurricane-affected areas falls nearly monotonically with wind speed, with the exception of a null coefficient on Category 2 wind speeds.[22] For the highest wind speed bin, the coefficient is -0.265, implying a reduction in total activity of $100 \cdot [\exp(-0.265) - 1] = -23.28$ percent. The coefficient on the spillover term $(1 - h_{zt})d_{zt}^{-1}$ is -0.044 and is significant at the 5 percent level, but excluding it does not change the main coefficient estimates. Table A1 in Appendix A reports full regression results.

3.3 Demographic heterogeneity

Individuals may differ in their responsiveness to hurricanes and evacuation orders. Prior surveys and case studies have found mixed results regarding heterogeneity of evacuation by race (Huang, Lindell, and Prater 2016; Thompson, Garfin, and Silver 2017). Anand et al. (2024) conclude that researchers must exercise caution when interpreting socioeconomic differences in evacuation due to idiosyncrasies between each hurricane and local area. They call for future research to control more carefully for physical storm characteristics to assess whether larger patterns persist.

A regression framework is well-suited to account for storm characteristics and unobservable local traits. In Appendix C, we explore heterogeneity in outmigration by separately estimating Equation 2 and interacting demographic quartile bins with each wind speed bin and evacuation order indicator. Specifically, we use the block group share with a bachelor's degree, the median household income, and the percent black, Hispanic, or white. In addition, we interact an indicator variable equal to one if the block group had greater than 50 percent urban population. Estimates produce wide confidence intervals due to the large number of interaction variables, which include wind speed, evacuation orders, and demographic bins. While generally not statistically different, some qualitative patterns emerge between groups.

To summarize, for severe hurricanes, higher income and higher education neighborhoods show larger responses to mandatory evacuation orders, consistent with results in Yabe and Ukkusuri (2020) and Younes, Darzi, and Zhang (2021). This result could speak to greater ability to evacuate, higher knowledge of hurricane risk, or more trust in government information. An alternative interpretation is that education and income are highly correlated with

22. Figure 4 plots the number of block group by week observations in each wind speed bin.

urbanicity. Urban block groups show much larger responses to high severity hurricanes compared to rural block groups, possibly due to greater physical risk in urban areas. Similarly, we observe qualitatively larger evacuation responses for non-white block groups, which could also correlate with urban areas, although effects between bins are generally not statistically different. These effects appear not to be driven by composition effects, for example if specific hurricanes in Florida were to have affected primarily Hispanic neighborhoods. Notably, no demographic group is responsive to voluntary evacuations at low to moderate wind speeds. See Appendix C for additional discussion.

4 Structural Estimation

In this section we model an individual's decision to evacuate or shelter during a hurricane. Utility is derived from 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 and sheltering.

4.1 Modeling approach

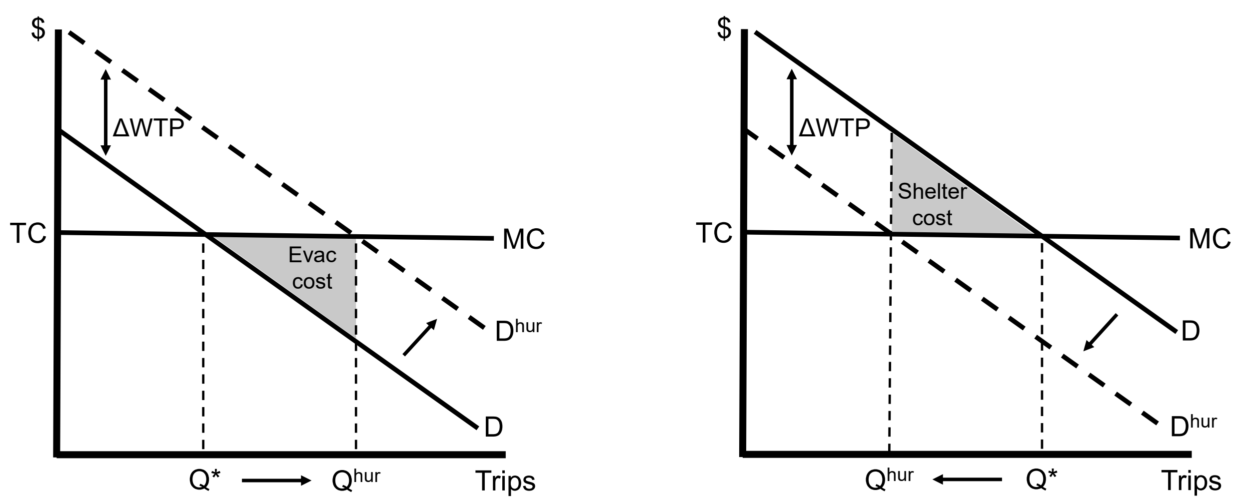
Consider the demand to travel from a fixed origin point z to a fixed destination j. Figure 3 plots this relationship with downward-sloping demand D, where the horizontal axis represents the number of trips taken from z to j and the vertical axis is the travel cost of a trip. The demand curve need not be linear. In this system, the marginal cost of a trip is constant at $MC = TC$, with an equilibrium number of trips Q^* at the intersection of D and MC.

A hurricane at origin z could induce either evacuation or sheltering behavior. Panel (a) depicts the case of evacuation. In this scenario, a severe hurricane raises the demand to move from z to j, shifting D outward to D^{hur}. This shift results in excess trips, $Q^{hur} > Q^*$, with welfare loss indicated by the shaded region where MC exceeds counterfactual demand D. The change in the willingness to pay (WTP) is the vertical distance between the demand curves, ΔWTP.

For mild storms, demand for movement may decrease, as illustrated by panel (b). Under a sheltering scenario, D^{hur} lies below D, resulting in fewer trips from z to j, $Q^{hur} < Q^*$. The welfare loss is again indicated by the shaded region, where in this case the counterfactual demand D would have exceeded MC between Q^{hur} and Q^*. Because demand has shifted downward, ΔWTP will take the opposite sign as in the evacuation scenario of panel (a).

Figure 3: Demand to travel from origin z to destination j

(a) Evacuation (b) Sheltering



Notes: The demand to move from a fixed origin z to a fixed destination j is indicated by the downward-sloping curve D. The horizontal quantity axis plots the number of trips from z to j, while the vertical price axis plots the travel cost from z to j. The marginal cost of a trip is fixed at the travel cost, $MC = TC$. Panel (a) depicts the case of evacuation, where demand shifts outward from D to D^{hur}, creating welfare loss indicated by the shaded region between MC and D. Panel (b) illustrates the case of sheltering, where demand shifts inward from D to D^{hur}, resulting in welfare loss in the shaded region between D and MC. See text for additional detail.

4.2 Utility parameterization

To estimate demand parameters, we model an individual's discrete choice of movement as a function of hurricane conditions. At time t, an individual i chooses whether to visit geographic location j. Define utility as:

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt}, \tag{4}$$

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:

$$V_{ijt} = \begin{cases} \alpha c_{ijt} + \beta h_{jt} + \delta_j + \lambda_t + \xi_{z(i),j,t}, & j \in \{1, 2, ..., J\}; \\ \varphi h_{z(i),t} + \delta_{z(i)}, & j = 0, \end{cases} \tag{5}$$

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. 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 $= \varphi/\alpha$.

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

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

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:

$$s_{zjt} = \frac{\exp(V_{ijt})}{\exp(V_{i0t}) + \sum_{k=1}^{J} \exp(V_{ikt})}. \tag{7}$$

Taking logs, we have:

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

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

$$\ldots$$

$$\log(s_{zJt}) = V_{iJt} - \log(\exp(V_{i0t}) + \sum_{k=1}^{J} \exp(V_{ikt})). \tag{8}$$

Differencing these logged shares yields a linear equation:

$$\begin{aligned}\log(s_{zjt}) - \log(s_{z0t}) &= V_{ijt} - V_{i0t} \\ &= \alpha c_{ijt} - \varphi h_{z(i),t} + \beta h_{jt} + \delta_j - \delta_{z(i)} + \lambda_t + \xi_{z(i),j,t}.\end{aligned} \tag{9}$$

Under the assumption that $\xi_{z(i),j,t}$ is distributed normally, Equation 9 can be estimated with ordinary least squares.

The empirical application uses flows of travel from origin block group z to destination county j in week and year t. An observation consists of a block group origin by county destination pair for a given week 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. Because it is a discrete choice problem, we frame a device's unique choice as its farthest observed destination in a given week, which eliminates attribution of the full travel cost to intermediate visits. 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.

4.3 Zero market shares

Recent work has highlighted the challenge to estimation of Equation 9 when data contain zero market shares $s_{zjt} = 0$, i.e. periods in which no member of market z is observed to have chosen j. Ignoring zero market shares introduces bias by omitting rejected alternatives (Li 2023). Mechanically, inclusion of only the selected choice alternatives creates a sample selection issue where the criterion for inclusion is $s_{zjt} > 0$, attenuating estimates of demand parameters (Gandhi, Lu, and Shi 2023). However, it is not possible to include an observation of $s_{zjt} = 0$ in the estimation, since $\log(0)$ is undefined. A separate but related concern is that, in settings with cell phone movement data, zero market shares might arise due to sampling error. For some z by j by t cells, the true share might be greater than zero despite observing $s_{zjt} = 0$ in the sample.

One corrective approach proposed by Gandhi, Lu, and Shi (2023) is to bound the share using institutional knowledge, for example by asserting that the number of individuals moving from z to j could be no lower than one, and to test sensitivity for the upper bound. An alternative approach by Li (2023) replaces zero market shares using a Bayesian shrinkage estimator, where prior distributions are used to adjust posterior mean shares. In a travel cost demand setting with cell phone mobility data, Cheng and Wan (2026) use simulations to show that empirical Bayes posterior mean estimation minimizes bias compared to other common approaches, including geographic aggregation, dropping zeros, and bounding methods akin to Gandhi, Lu, and Shi (2023).

We follow the approach of Cheng and Wan (2026) and develop prior distributions for each block group by county by week pair. To form the prior distribution, we use the visit behavior of the 50 most "comparable" markets z, where comparability is defined as having a similar travel cost from z to j in time t. Define the number of visits from z to j in time t as K_{zjt}, which represents a draw from a binomial distribution with N_{zt} trials, where N_{zt} is the total number of observed visits from z in time t. As in Equations 6 and 7, the probability of a trip is s_{zjt}. Each s_{zjt} is distinct among z by j pairs and is drawn from a Beta prior distribution with hyperparameters γ^1_{zjt} and γ^2_{zjt}. The distributions of K_{zjt} and s_{zjt} are given by:

$$K_{zjt} \sim Binomial(N_{zt}, s_{zjt});$$
$$s_{zjt} \sim Beta(\gamma^1_{zjt}, \gamma^2_{zjt}). \tag{10}$$

The posterior distribution of the trip probability is:

$$\tilde{s}_{zjt} \sim Beta(\gamma^1_{zjt} + K_{zjt}, \gamma^2_{zjt} + N_{zt} - K_{zjt}), \tag{11}$$

and the posterior mean is:

$$\hat{s}_{zjt} = \frac{\gamma^1_{zjt} + K_{zjt}}{\gamma^1_{zjt} + \gamma^2_{zjt} + N_{zt}}. \tag{12}$$

Let μ_{zjt} and v_{zjt} be the mean and variance of visits to j in t among the 50 most comparable neighbors of z. Using method of moments, the hyperparameters are approximated as:

$$\hat{\gamma}^1_{zjt} = \Big(\frac{\mu_{zjt}(1-\mu_{zjt})}{v_{zjt}} - 1\Big)\mu_{zjt};$$
$$\hat{\gamma}^2_{zjt} = \Big(\frac{\mu_{zjt}(1-\mu_{zjt})}{v_{zjt}} - 1\Big)(1-\mu_{zjt}). \tag{13}$$

The use of method of moments is a departure from Li (2023) and Cheng and Wan (2026), who both used maximum likelihood estimation. At the scale of our data, method of moments provides a computationally tractable alternative. For empirical Bayes shrinkage estimators, method of moments has commonly been used to estimate Beta-binomial hyperparameters, and has been shown to be 95 percent efficient for the mean parameter (Kleinman 1973; Lu 1999; Morris 1983).

Following Connolly et al. (2026), we define the choice set for each origin z as the set of destinations j which were ever observed to have been chosen in a year, subject to a 500 mile distance cutoff. Given this choice set, we estimate hyperparameters γ^1_{zjt} and γ^2_{zjt} for every paired origin, destination, and week, giving strictly positive shares. Appendix E reports summary information and robustness checks for the empirical Bayes shrinkage estimator.

4.4 Estimation of utility parameters

Operationally, we elaborate on Equation 9 to capture the same risk dynamics of the reduced form analysis. As in Equation 2, we include wind speed bins $H^b_{zt} \equiv h_{zt} \cdot \mathbb{1}\{wind_{zt} \in b\}$ for bins $b \in B$, as well as evacuation indicators O^{Vol}_{zt} and O^{Man}_{zt}. To saturate the regression, we also interact hurricane indicators at the origin and destination with a continuous measure of the wind speed differential, $h_{zt}h_{jt}(wind_{jt} - wind_{zt})$, which allows for cleaner interpretation of the uninteracted hurricane coefficients at origin and destination. Using the empirical Bayes shares $\hat{s}_{zjt}$, the estimating equation is:

$$\log(\hat{s}_{zjt}) - \log(\hat{s}_{z0t}) = \alpha c_{zjt} + \sum_{b \in B} H^b_{zt}(\varphi_b + \varphi^{Vol}_b O^{Vol}_{zt} + \varphi^{Man}_b O^{Man}_{zt})$$

$$+ \beta h_{jt} + \omega h_{zt}h_{jt}(wind_{jt} - wind_{zt}) + \delta_j + \delta_z + \lambda_t + \xi_{zjt}. \qquad (14)$$

This equation generates multiple WTP estimates, for instance $(\varphi_b + \varphi^{Man}_b)/\alpha$, given various wind speed bins. Standard errors are computed using the delta method.

We restrict the data in two ways. First, because almost all of the observed tropical storms occur during the months of June to November, we limit attention to these months for the years 2019 to 2023. Second, we use only origin-destination pairs that are within 500 miles of driving distance, as described in Section 2.5.[23] The estimating dataset consists of 52.6 million observations when ignoring zero market shares, and 274.4 million observations after Bayesian posterior mean estimation.

The identification assumption is that hurricane conditions and travel costs are exogenous conditional on fixed effects that control for average traits of individuals by origin zone, unobserved qualities of each destination, and time-varying factors common to all units. Parameters of interest are constant across individuals, which comes from an assumption of preference homogeneity. 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 residents.

23. 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.

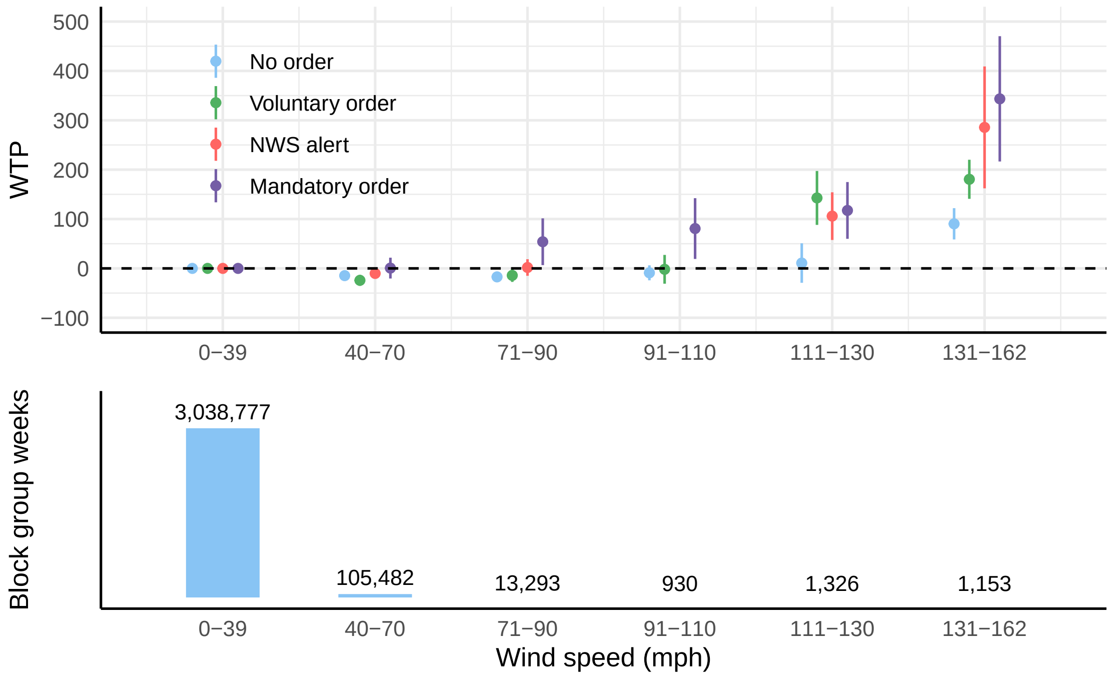
4.5 Welfare cost of evacuation and sheltering

Figure 4 plots WTP values derived from estimation of Equation 14, where WTP is computed based on the ratio of the marginal disutility in hurricane exposure to the marginal disutility of expenditure. These values are allowed to vary by the severity of tropical storm and information treatment in the same way as the reduced form analysis of Figure 2. Full regression results are reported in Table A2 Appendix A.

Per-person welfare costs rise with the severity of hurricane. When subject to mandatory evacuation orders, welfare costs rise to $117 per person for Category 3 winds and $343 per person for Category 4 and 5 winds. Voluntary evacuation orders also show large compliance at high wind speeds, with welfare costs of $143 to $180 per person at Category 3 winds and above. As with previous analyses, we separately estimate a version of Equation 14 with NWS alerts, finding that welfare values resemble those for evacuation orders at high wind speeds and voluntary or no order at low speeds.

At low wind speeds, welfare costs take the opposite sign, consistent with the sheltering predictions of Figure 3. In absolute value, these costs are largest for mild to moderate severity wind speeds and when individuals are subject to no order or voluntary evacuation orders. For example, sheltering costs are between $10 and $24 per person at tropical storm force winds, and $14 to $17 per person at wind speeds of 71 to 90 miles per hour, which is approximately Category 1. On a per-person basis, these costs are much smaller than in the case of evacuation. However, many more individuals experience mild to moderate wind speeds, as shown by the lower panel of Figure 4. In Section 5 we show that total sheltering costs greatly exceed total evacuation costs in the aggregate.

Figure 4: Welfare costs of hurricane evacuation and sheltering



Notes: Welfare costs of evacuation rise with hurricane severity and when individuals are subject to evacuation orders. Full regression results are reported in Table A2 in Appendix A. Welfare effects for each bin and category are reported in Table A3 in Appendix A. Standard errors are computed using the delta method. N = 274,362,140.

4.6 Robustness

We perform several robustness checks. First, following the recommendations of Lupi, Phaneuf, and von Haefen (2020), we show sensitivity to the value of travel time, p^T_{zt}, which is a main component of the travel cost calculation in Equation 1. No broad agreement exists for the correct value of travel time in travel cost demand analyses. While many recreation applications use one-third the wage rate, the US Department of Transportation recommends a value of one-half the wage rate in transportation settings (Lupi, Phaneuf, and von Haefen 2020). Because our analysis constructs estimates using counterfactual commuting behavior, we use one-half the wage rate as the preferred measure. However, Table A4 in Appendix A shows that adjusting this factor to either one-third or two-thirds predictably changes the travel cost coefficient, which consequently affects welfare estimates.

The travel cost bounds of Table A4 are also informative about the potential effects of traffic congestion. Wu, Lindell, and Prater (2012) and Rahman, Roy, and Hasan (2021) studied traffic congestion during Hurricanes Katrina, Rita, and Irma, finding that travel times increased by a factor of 1.5, 2.7, and 1.4, respectively, relative to normal conditions. If congestion increases travel times during a hurricane, this would favor a higher travel cost in the analysis, which lowers the coefficient estimate and inflates welfare values. For example, under a higher assumption of the value of travel time in Table A4, welfare costs rise to \$428 per person under mandatory evacuation orders for Category 4 and 5 winds, compared to \$343 in the intermediate case.

A further issue relates to sample representativeness (Bayham, Enriquez, and Richardson 2026). As discussed in Section 2.1, both Cuebiq and Advan data have been found to be demographically and spatially representative of the US population (Hsu et al. 2024; Kang et al. 2020; Squire 2019). However, in Appendix B, we report summary statistics for our specific study area. The Cuebiq data and Advan data reflect, respectively, 2.7 million and 4.3 million devices per year in our study area, which is about 6.2 percent and 9.8 percent of the population. For both providers, a block group's count of devices correlates strongly to the Census-reported population, but white block groups are slightly overrepresented and black and Hispanic block groups are slightly underrepresented, with no differences by income. If demographic groups differ systematically in their preferences, welfare estimates could either be over- or understated. Appendix C explores differences in evacuation based on block group demographics, which partially speaks to this issue. Although evacuation responses are not statistically different between quartiles of race, non-white block groups show somewhat larger responses. If non-white individuals are more likely to evacuate, under-sampling them would yield lower bound welfare estimates. However, because estimates are not statistically different, we do not conclude that welfare estimates are affected by sample representativeness.

Separately, we assess the dynamic effects of hurricanes for movement. The discrete choice model of Equation 5 implies that tropical storms only affect utility contemporaneously, that is, in the week of a storm. We explore the extent to which this assumption holds. In Appendix D we estimate distributed lag models for the reduced form variables of Section 3 (Schmidheiny and Siegloch 2023). For low to moderate wind speeds, movement activity quickly returns to baseline levels after one week. However, for Category 3 and greater winds, device behavior is observably altered for several weeks. These patterns could be consistent with extended recovery and rebuilding activity (Roth Tran and Wilson 2025). One potential treatment of this issue would be to include dynamic components of utility, for example lagged hurricane indicators. However, we cannot rule out that devices stay outside the home area for several weeks, for example at a close friend or relative's property. Because discrete choice models attribute the full travel cost of a trip to each choice occasion, introducing a lag structure could overstate travel expenditures in the presence of chained trips or extended stays. Therefore, we code only the contemporaneous period as hurricane-affected, which we consider to be conservative.

Lastly, in Appendix E, we document some features of the Bayesian shrinkage estimator for zero market shares. The first exercise reports results when simply dropping the zero market shares. Consistent with predictions by Cheng and Wan (2026), ignoring zero market shares attenuates demand parameters, particularly the travel cost coefficient. The net effect would be to inflate WTP values, yielding estimates of up to \$409 per person for evacuation and \$55 per person for sheltering.

In light of these differences, one question is whether the Bayesian shrinkage estimator actually has a perverse effect by downward biasing large movement shares during an evacuation and upward biasing small movement shares during a sheltering event. To test this possibility, we regress the difference between the adjusted Bayesian shares and the observed shares, $(\hat{s}_{zjt} - s_{zjt})$, on hurricane and evacuation order indicators. Table E3 in Appendix E reports the results. Coefficients are close to precise zeros; the largest magnitude coefficient is 0.0022, which, when compared to the travel cost coefficient in the main estimation, would yield a WTP difference of $0.0022/0.005 = \$0.44$. We consider this result to be evidence against shrinkage bias.

5 Total Cost of Hurricane Evacuation and Sheltering

We generate back-of-the-envelope calculations for the total cost of hurricane evacuation using the empirical WTP estimates of Section 4. We apply estimates according to whether a block group was hurricane-affected and whether it received a voluntary or mandatory evacuation order. 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. For this analysis, we include hurricane-affected areas across the entire portion of the eight states in the analysis, rather than just areas within 100 miles of the coast; however, costs for other potentially affected states are not included.[24] These cost 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 2 displays the welfare costs of evacuation by storm. Evacuation costs range from \$11 million to \$133 million for Category 3 and greater hurricanes, amounting to nearly half a billion dollars over the study period. These estimates generally increase with the severity of a storm. While the per-person costs of sheltering are much lower than evacuation, in the aggregate the costs of sheltering far exceed the costs of evacuation. Over the study period the total sheltering costs are approximately \$1.8 billion.

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. In most cases, the costs of evacuation and sheltering are small when compared to the total property damage. Of relevance for emergency management is the comparison to mortality costs. In some cases the cost of evacuation and sheltering is substantial when compared to mortality costs, occasionally surpassing VSL entirely. On average, the ratio of evacuation and sheltering costs to mortality is about 55 to 100.

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. Still, the estimates of Table 2 provide context for the magnitude of evacuation and sheltering costs.

24. Welfare estimates can be computed directly for the block groups in the sample, with expected compensating variation given by $CV_{it} = -\frac{1}{\alpha}\big(\mathbb{E}[\max_j U_{ijt}(h_{z(i),t} = 1)] - \mathbb{E}[\max_j U_{ijt}(h_{z(i),t} = 0)]\big)$. However, this computation omits other affected areas for the eight states.

Table 2: Hurricane evacuation and sheltering costs compared to property damage and VSL

Storm	Cat.	Year	Cost of evac. (millions)	Cost of shelter (millions)	Property damage (millions)	As percent of property (%)	Deaths	VSL (millions)	As percent of VSL (%)
Ida	4	2021	133.2	40.7	81,945	0.21	96	1,075	16.2
Ian	5	2022	119.5	303.2	114,774	0.37	152	1,702	24.8
Laura	4	2020	81.4	29.3	27,215	0.41	42	470	23.5
Dorian	4	2019	51.4	64.4	1,912	6.06	10	112	103.4
Nicole	1	2022	31.3	253.8	1,044	27.31	5	56	509.1
Idalia	4	2023	18.7	200.8	3,430	6.40	5	56	391.9
Delta	3	2020	16.8	65.0	3,355	2.44	5	56	146
Zeta	3	2020	11.0	160.4	5,093	3.37	6	67	255.1
Barry	1	2019	7.9	48.0	713	7.85	2	22	249.8
Sally	2	2020	0.1	29.2	8,516	0.34	5	56	52.3
Eta	1	2020	0.0	228.1	1,710	13.35	12	134	169.7
Elsa	1	2021	0.0	131.9	1,354	9.74	1	11	1177.6
Isaias	1	2020	0.0	120.4	5,577	2.16	16	179	67.2
Nicholas	1	2021	0.0	89.4	1,129	7.92	0	0	
Hanna	1	2020	0.0	20.8	1,264	1.65	0	0	
Fred	0	2021	0.0	19.5	1,422	1.37	7	78	24.9
Imelda	0	2019	0.0	0.2	5,934	0.00	5	56	0.3
Total			471.3	1,805.1	266,384	0.85	369	4,133	55.1

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 Figure 4 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 and sheltering. 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 evacuation and sheltering can be several hundred million dollars per storm. When compared to mortality, evacuation and sheltering costs average a ratio of 55 to 100, 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, 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. Rather than assessing travel to specific sites of interest, we estimate utility parameters from fully generalizable movement throughout space.

We have spoken to a few key literatures, but it is worthwhile to further situate the 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, Kawano, and Levitt 2018; Gallagher and Hartley 2017; Groen, Kutzbach, and Polivka 2020; Peri, Rury, and Wiltshire 2024; 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 2025). 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 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 single 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”

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15 September 2026

Appendix A: Additional Figures A2

Appendix B: Device Summary Statistics A8

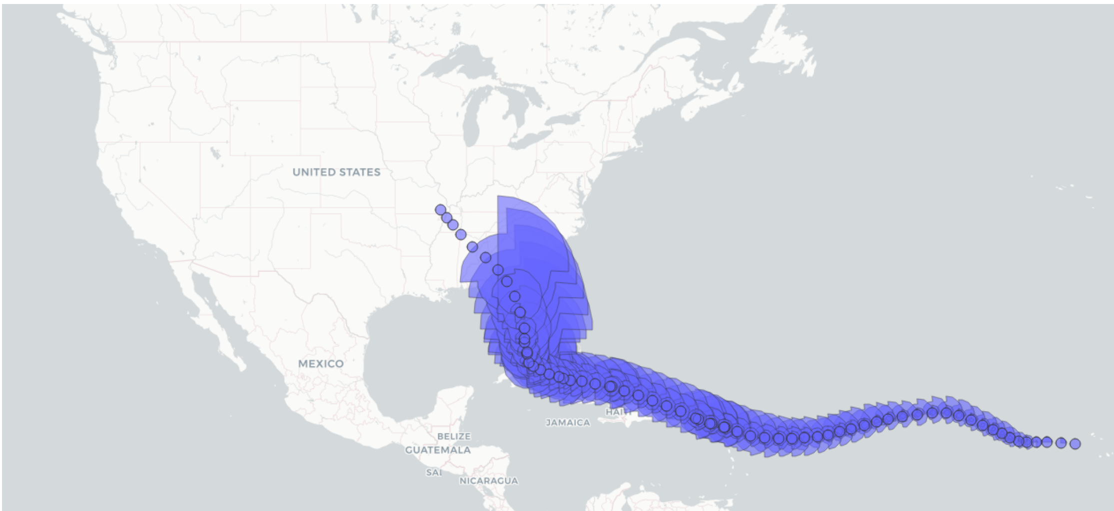
Appendix C: Demographic Heterogeneity A10

Appendix D: Dynamic Effects of Hurricanes A16

Appendix E: Zero Market Shares A18

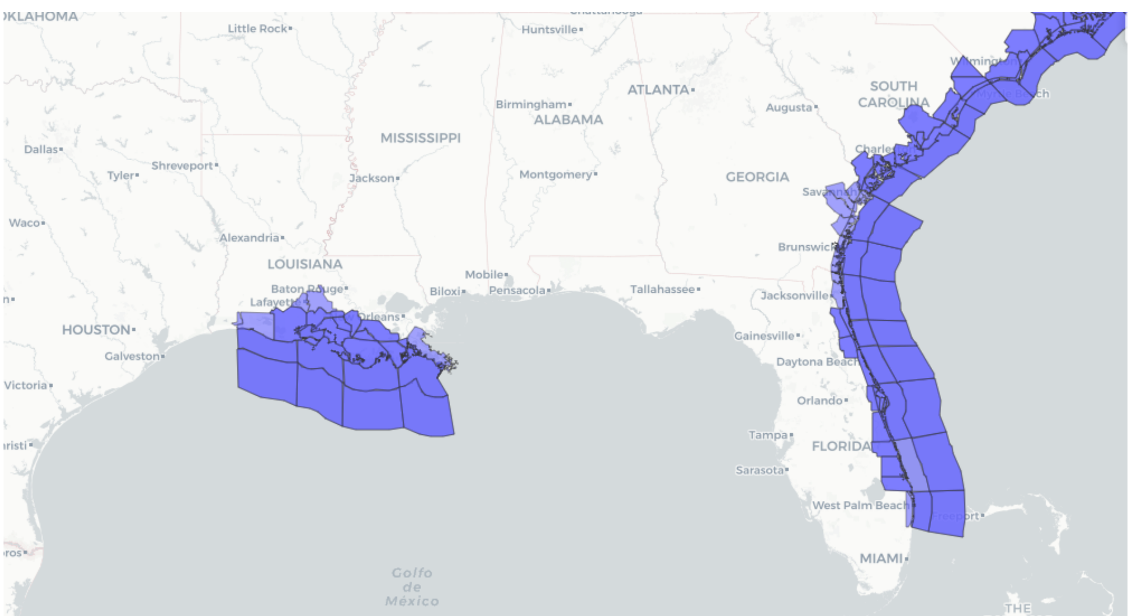
Appendix A: Additional Figures

Figure A1: Example raw data for hurricane path



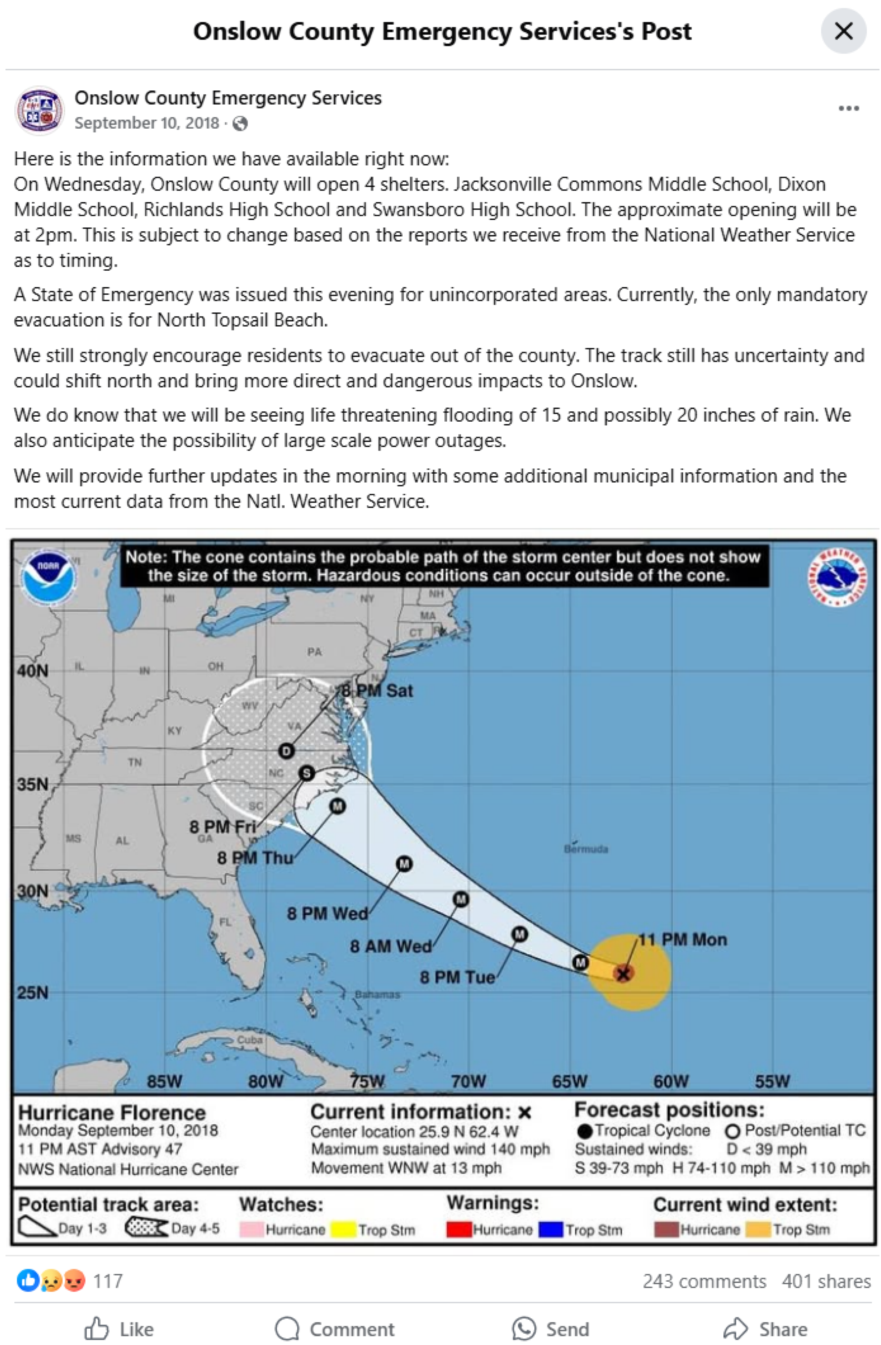
Notes: Example raw points and radii data from NOAA's National Hurricane Center (NHC) Best Track Data (HURDAT2). These data report, at six hour intervals, the path of a storm, as well as wind speed radii associated with 34-, 50-, and 64-knot winds. They also contain information on peak wind speeds.

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



Notes: Example raw data for NWS alerts for hurricanes during 2019. The polygons plot boundaries for public zones, which are often identical to counties, but can be more spatially granular near the coastline.

Figure A3: Example hurricane evacuation order on social media



Notes: Example evacuation order on social media. In this case, emergency managers asked all residents to leave the county. The post also illustrates the transmission of upstream information from NWS to downstream local officials.

Table A1: Reduced form regressions for outmigration and foot traffic

	s^0_{zt}	s^0_{zt}	$dist^{75}_{zt}$	$dist^{75}_{zt}$	$\log(visits_{zt})$
Storm path × Wind spd 40-70	0.022***	0.022***	-2.328***	-2.193***	-0.043***
	(0.002)	(0.002)	(0.344)	(0.354)	(0.008)
Storm path × Wind spd 71-90	0.035***	0.030***	0.428	0.905	-0.111***
	(0.006)	(0.007)	(1.746)	(1.751)	(0.013)
Storm path × Wind spd 91-110	0.033***	-0.002	1.359	17.041**	-0.016
	(0.007)	(0.024)	(1.729)	(7.450)	(0.043)
Storm path × Wind spd 111-130	0.053***	0.072***	13.195	-1.975	-0.148***
	(0.016)	(0.014)	(14.330)	(3.815)	(0.033)
Storm path × Wind spd 131-162	-0.022	-0.019	41.200***	38.312***	-0.265***
	(0.028)	(0.029)	(11.064)	(11.406)	(0.051)
Not in storm path × Inverse dist.					-0.044**
					(0.018)
Storm path × Wind spd 40-70 × Vol. evac. order	0.008		-2.390		
	(0.006)		(1.522)		
Storm path × Wind spd 71-90 × Vol. evac. order	0.003		-0.654		
	(0.008)		(2.796)		
Storm path × Wind spd 91-110 × Vol. evac. order	-0.004		6.941		
	(0.019)		(4.798)		
Storm path × Wind spd 111-130 × Vol. evac. order	-0.103***		152.299***		
	(0.030)		(39.363)		
Storm path × Wind spd 131-162 × Vol. evac. order	-0.078**		185.978***		
	(0.030)		(35.258)		
Storm path × Wind spd 40-70 × Man. evac. order	-0.010		14.226**		
	(0.010)		(5.730)		
Storm path × Wind spd 71-90 × Man. evac. order	-0.059**		44.244**		
	(0.026)		(17.969)		
Storm path × Wind spd 91-110 × Man. evac. order	-0.132**		51.091***		
	(0.066)		(18.173)		
Storm path × Wind spd 111-130 × Man. evac. order	-0.108***		149.624***		
	(0.033)		(41.234)		
Storm path × Wind spd 131-162 × Man. evac. order	-0.277***		181.589***		
	(0.095)		(19.327)		
Storm path × Wind spd 40-70 × NWS alert		0.0004		3.726	
		(0.005)		(2.292)	
Storm path × Wind spd 71-90 × NWS alert		-0.004		12.125**	
		(0.012)		(5.671)	
Storm path × Wind spd 111-130 × NWS alert		-0.105***		130.820***	
		(0.027)		(32.813)	
Storm path × Wind spd 131-162 × NWS alert		-0.202**		170.761***	
		(0.088)		(24.260)	
Block group orig. FE	Yes	Yes	Yes	Yes	Yes
Week-year FE	Yes	Yes	Yes	Yes	Yes
Dep. var. mean	0.51	0.51	47.2	47.2	5553
N	3,157,580	3,157,580	3,157,580	3,157,580	3,157,477

Notes: Reduced form regressions corresponding to Figure 2. Wind speed is reported in miles per hour. The dependent variables are the share staying home s^0_{zt}, the 75th percentile of distance traveled $dist^{75}_{zt}$, and foot traffic $\log(visits_{zt})$. Standard errors are clustered by origin county. Weights are by block group population. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Structural estimation of marginal utility in evacuation

	(1)	(2)
Travel cost (dollars)	-0.005***	-0.005***
	(0.0001)	(0.0001)
Storm path (dest.)	-0.066***	-0.065***
	(0.004)	(0.004)
Storm path (orig.) × Storm path (dest.) × Wind spd diff.	0.003***	0.002***
	(0.001)	(0.001)
Storm path (orig.) × Wind spd 40-70	-0.073***	-0.074***
	(0.006)	(0.006)
Storm path (orig.) × Wind spd 71-90	-0.086***	-0.069***
	(0.021)	(0.024)
Storm path (orig.) × Wind spd 91-110	-0.045	0.114
	(0.039)	(0.078)
Storm path (orig.) × Wind spd 111-130	0.054	-0.143***
	(0.102)	(0.051)
Storm path (orig.) × Wind spd 131-162	0.451***	0.413***
	(0.081)	(0.077)
Storm path (orig.) × Wind spd 40-70 × Vol. evac. order	-0.047*	
	(0.028)	
Storm path (orig.) × Wind spd 71-90 × Vol. evac. order	0.015	
	(0.040)	
Storm path (orig.) × Wind spd 91-110 × Vol. evac. order	0.036	
	(0.080)	
Storm path (orig.) × Wind spd 111-130 × Vol. evac. order	0.658***	
	(0.168)	
Storm path (orig.) × Wind spd 131-162 × Vol. evac. order	0.450***	
	(0.119)	
Storm path (orig.) × Wind spd 40-70 × Man. evac. order	0.076	
	(0.054)	
Storm path (orig.) × Wind spd 71-90 × Man. evac. order	0.355***	
	(0.121)	
Storm path (orig.) × Wind spd 91-110 × Man. evac. order	0.447***	
	(0.165)	
Storm path (orig.) × Wind spd 111-130 × Man. evac. order	0.532***	
	(0.184)	
Storm path (orig.) × Wind spd 131-162 × Man. evac. order	1.263***	
	(0.336)	
Storm path (orig.) × Wind spd 40-70 × NWS alert		0.023
		(0.024)
Storm path (orig.) × Wind spd 71-90 × NWS alert		0.078
		(0.048)
Storm path (orig.) × Wind spd 111-130 × NWS alert		0.671***
		(0.133)
Storm path (orig.) × Wind spd 131-162 × NWS alert		1.012***
		(0.326)
Block group orig. FE	Yes	Yes
County dest. FE	Yes	Yes
Week-year FE	Yes	Yes
N	274,362,140	274,362,140

Notes: Regression for structural estimation corresponding to Figure 4 and Table A3. Wind speed is reported in miles per hour. 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. The dependent variable is $\log(\hat{s}_{zjt}) - \log(\hat{s}_{z0t})$. 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Summary of WTP estimates

Wind speed	No order	Voluntary order	NWS alert	Mandatory order
40-70	-14.67***	-24.19***	-10.21**	0.65
	(1.16)	(5.67)	(4.78)	(10.76)
71-90	-17.17***	-14.15**	1.84	54.01**
	(4.09)	(6.74)	(8.56)	(24.16)
91-110	-8.97	-1.84		80.70**
	(7.75)	(14.87)		(31.40)
111-130	10.86	142.71***	105.89***	117.40***
	(20.42)	(27.84)	(24.62)	(29.34)
131-162	90.30***	180.49***	285.62***	343.46***
	(16.16)	(20.19)	(62.98)	(64.74)

Notes: Summary of WTP estimates corresponding to Figure 4 and Table A2. 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Structural estimation of marginal util. in evac., sensitivity to val. of travel time

	$\frac{1}{3}$ wage rate	$\frac{1}{2}$ wage rate	$\frac{2}{3}$ wage rate
Travel cost (dollars)	-0.006***	-0.005***	-0.004***
	(0.0001)	(0.0001)	(0.0001)
Storm path (dest.)	-0.065***	-0.066***	-0.066***
	(0.004)	(0.004)	(0.004)
Storm path (orig.) × Storm path (dest.) × Wind spd diff.	0.002***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)
Storm path (orig.) × Wind spd 40-70	-0.074***	-0.073***	-0.073***
	(0.006)	(0.006)	(0.006)
Storm path (orig.) × Wind spd 71-90	-0.089***	-0.086***	-0.084***
	(0.021)	(0.021)	(0.021)
Storm path (orig.) × Wind spd 91-110	-0.049	-0.045	-0.042
	(0.038)	(0.039)	(0.039)
Storm path (orig.) × Wind spd 111-130	0.051	0.054	0.056
	(0.102)	(0.102)	(0.102)
Storm path (orig.) × Wind spd 131-162	0.444***	0.451***	0.455***
	(0.082)	(0.081)	(0.080)
Storm path (orig.) × Wind spd 40-70 × Vol. evac. order	-0.048*	-0.047*	-0.047*
	(0.028)	(0.028)	(0.029)
Storm path (orig.) × Wind spd 71-90 × Vol. evac. order	0.014	0.015	0.016
	(0.039)	(0.040)	(0.040)
Storm path (orig.) × Wind spd 91-110 × Vol. evac. order	0.039	0.036	0.033
	(0.080)	(0.080)	(0.080)
Storm path (orig.) × Wind spd 111-130 × Vol. evac. order	0.658***	0.658***	0.657***
	(0.168)	(0.168)	(0.168)
Storm path (orig.) × Wind spd 131-162 × Vol. evac. order	0.458***	0.450***	0.444***
	(0.119)	(0.119)	(0.120)
Storm path (orig.) × Wind spd 40-70 × Man. evac. order	0.077	0.076	0.076
	(0.053)	(0.054)	(0.054)
Storm path (orig.) × Wind spd 71-90 × Man. evac. order	0.357***	0.355***	0.354***
	(0.121)	(0.121)	(0.121)
Storm path (orig.) × Wind spd 91-110 × Man. evac. order	0.453***	0.447***	0.444***
	(0.166)	(0.165)	(0.165)
Storm path (orig.) × Wind spd 111-130 × Man. evac. order	0.534***	0.532***	0.530***
	(0.184)	(0.184)	(0.184)
Storm path (orig.) × Wind spd 131-162 × Man. evac. order	1.271***	1.263***	1.258***
	(0.337)	(0.336)	(0.335)
Block group orig. FE	Yes	Yes	Yes
County dest. FE	Yes	Yes	Yes
Week-year FE	Yes	Yes	Yes
N	274,362,140	274,362,140	274,362,140

Notes: Regression for structural estimation corresponding to Figure 4 and Table A2, showing sensitivity to the value of travel time. The value of travel time is varied between one-third, one-half, and two-thirds the wage rate. Wind speed is reported in miles per hour. 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. The dependent variable is $\log(\hat{s}_{zjt}) - \log(\hat{s}_{z0t})$. 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix B: Device Summary Statistics

Much of the literature has found that Cuebiq and Advan, the data providers used for this analysis, are spatially and temporally representative of the US population (Hsu et al. 2024; Kang et al. 2020; Squire 2019). However, we assess some measures of sample representativeness in this appendix.

Table B1 reports summary statistics for each provider. The average block group by week observation contains approximately 109 devices for Cuebiq and 169 devices for Advan. In the aggregate, the study area draws from approximately 2.7 million and 4.3 million devices per year from each provider, representing 6.2 and 9.8 percent of the population, respectively. One check on sampling is to correlate the number of devices in a block group with its population. We find a high correlation in the case of Cuebiq, at 0.845, and a reasonable correlation in the case of Advan, at 0.697.

Table B1: Device coverage by block group

	Cuebiq	Advan
Average devices by block group	108.9	168.6
Number of block groups	25,498	25,498
Number of counties	342	342
Average total annual devices	2,739,334	4,299,176
Census total population	43,995,646	43,995,646
Total devices as proportion of total pop.	0.062	0.098
Correlation of block group devices and pop.	0.845	0.697

Notes: Average devices by block group are the average weekly number of devices reported by a block group over the study period. Number of block groups and number of counties represent unique numbers of administrative units. The average total annual devices is the average of the total number of devices by year for each provider. This figure is taken as a proportion of the total Census-reported population for the relevant block groups to give the total devices as a proportion of total population. The correlation coefficient represents the raw correlation between weekly device count and Census population. All population figures throughout the paper are relative to 2018.

A next issue concerns demographic representativeness. While we do not observe the demographic information for any particular device, we can assess whether block groups with certain demographic features are relatively over- or under-sampled. In Table B2, we regress the log of a block group's average number of weekly devices on the log of population, as well as Z-scored, standardized variables for the share black, share Hispanic, share white, and median income.

The coefficients on logged population are essentially elasticity measures, showing that for a 1 percent increase in population, there is a 0.910 or 0.848 increase in the number of devices in a block group. The Z-scored coefficients show that whiter areas tend to be sampled somewhat more than non-white areas, and that there is no difference by income after controlling for race.

To contextualize these magnitudes, note that the units are measured in terms of standard deviations. Therefore, a block group with a one standard deviation higher share of white population is expected to have 16.8 percent more devices in the Cuebiq data, holding all else equal. The standard deviation for share white, black, and Hispanic are all about 0.27, which is high given that the share can be at most 1; therefore, we expect this over- or under-sampling to primarily affect block groups that are very demographically concentrated.

In terms of effects on estimates, all estimates in the paper use block group fixed effects, which can control for some location-specific unobservables. More importantly, the dependent variables are normalized as shares. In that sense, the number of devices should not affect interpretation of the share variable. Under-sampling could introduce noise into share variables. However, to systematically bias estimates would require that preferences differ between white and non-white groups. The main estimation assumes preference homogeneity, but Appendix C explores potential demographic heterogeneity. While non-white block groups have somewhat higher evacuation responses, results are generally not statistically different. Overall, we do not view potential over- or under-sampling as a threat to the main estimates of the paper.

Table B2: Device coverage and demographic representativeness

	Cuebiq (1)	Advan (2)
Intercept	-2.196***	-1.317***
	(0.129)	(0.163)
log(Population)	0.910***	0.848***
	(0.017)	(0.021)
Black	-0.075**	-0.136***
	(0.032)	(0.034)
Hispanic	-0.137***	-0.143***
	(0.016)	(0.018)
White	0.168***	0.135***
	(0.037)	(0.038)
Median income	0.004	0.014
	(0.014)	(0.015)
N	24,426	24,426

Notes: Regression of log(number of devices) in a block group on log(population) and Z-scored, standardized variables for share of block group that is black, share Hispanic, share white, and median income. The units on demographic variables are per one standard deviation. Standard errors are clustered by origin county. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix C: Demographic Heterogeneity

Section 3.3 discusses potential heterogeneity in evacuation behavior for various demographic groups. This section re-estimates the reduced form regressions of Equation 2, interacting quartile bins for demographic heterogeneity based on block group characteristics. We focus on education, income, urbanicity, and race.

One potential econometric concern is that any analysis using between-storm demographic variation might over-interpret composition effects, even after conditioning on wind speed and evacuation orders. For example, responses for the top quantile of Hispanic block groups might reflect specific storms in Florida, whereas the top quantile of black block groups might capture Louisiana storms. However, when regressing the share of a block group that is black or Hispanic on storm fixed effects, omitting observations with no storm, we find low R^2 values of 0.06 and 0.27, respectively. This exercise suggests that interacting quartiles of black or Hispanic block group population with the hurricane treatment variable does not suffer from composition effects.

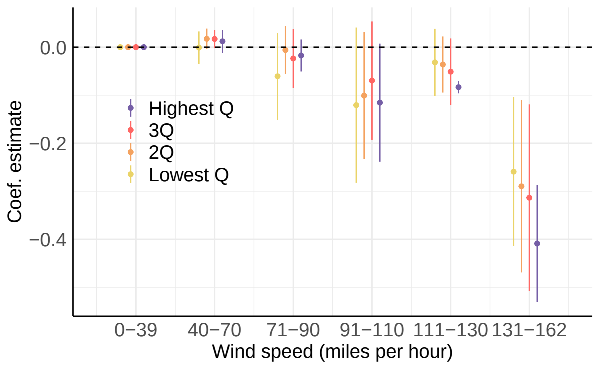
Figures C1 through C4 show coefficient plots of outmigration for education, income, urbanicity, and race. We focus on results for mandatory and voluntary evacuation orders. Across regressions, the exercise generates hundreds of coefficients, resulting in wide confidence intervals for the combined effects. While generally not statistically different, some qualitative patterns emerge between quartiles.

To summarize, higher education and higher income areas show somewhat higher responsiveness to evacuation orders at higher wind speeds. For example, under Category 4 and 5 winds, the highest quartile of neighborhoods by education shows a drop of 0.41 in the share staying home s^0_{zt}, compared to a drop of 0.26 for the lowest quartile.

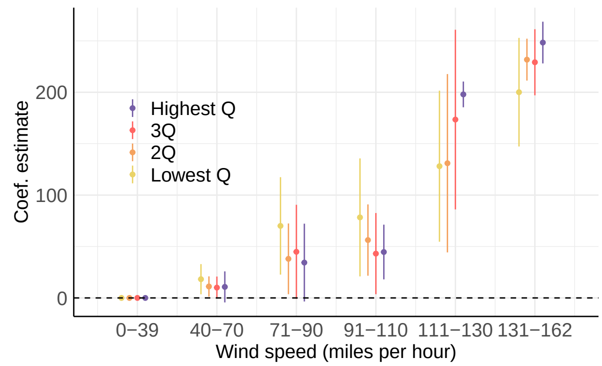
However, these effects could be explained by differences between urban and rural areas, which have different levels of physical risk. Panels (e) and (f) of Figure C1 show that urban block groups are more responsive to mandatory evacuation orders, a pattern which is repeated in Figure C3 for voluntary evacuation orders. Similarly, the disparity between urban and rural areas could explain the results by race; across Figures C2 and C4, non-white areas show greater levels of outmigration for both mandatory and voluntary evacuation orders. We view these results as weakly suggestive but not dispositive evidence of demographic differences in outmigration.

Figure C1: Responses to mandatory evacuation orders by education, income, and urbanicity

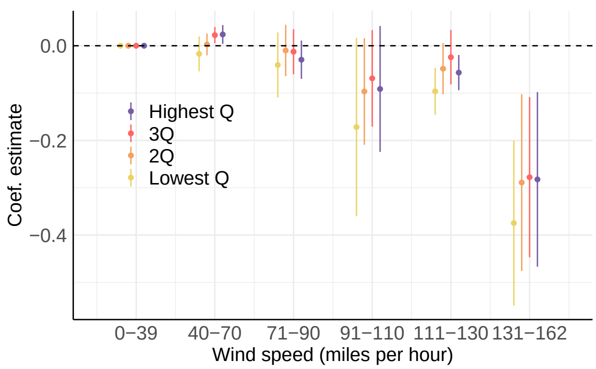
(a) Share staying home, het. by education



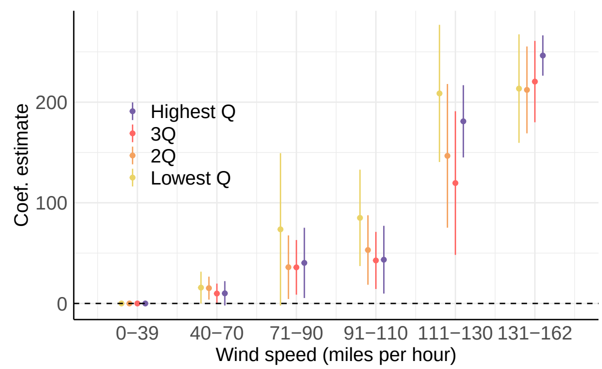
(b) Dist. traveled, het. by education



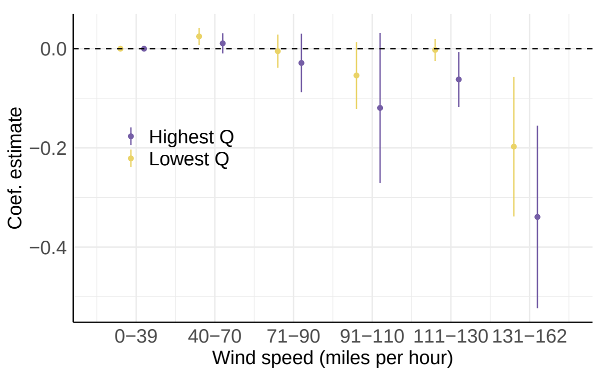
(c) Share staying home, het. by income



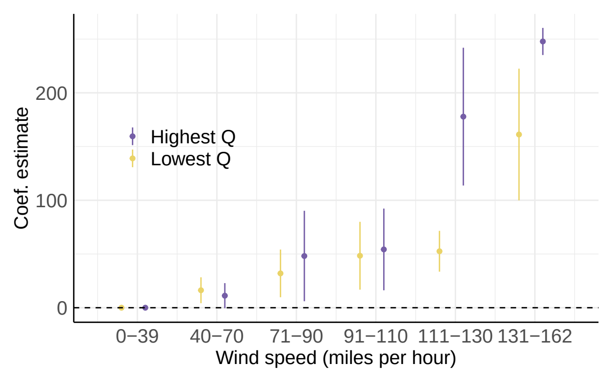
(d) Dist. traveled, het. by income



(e) Share staying home, het. by urbanicity

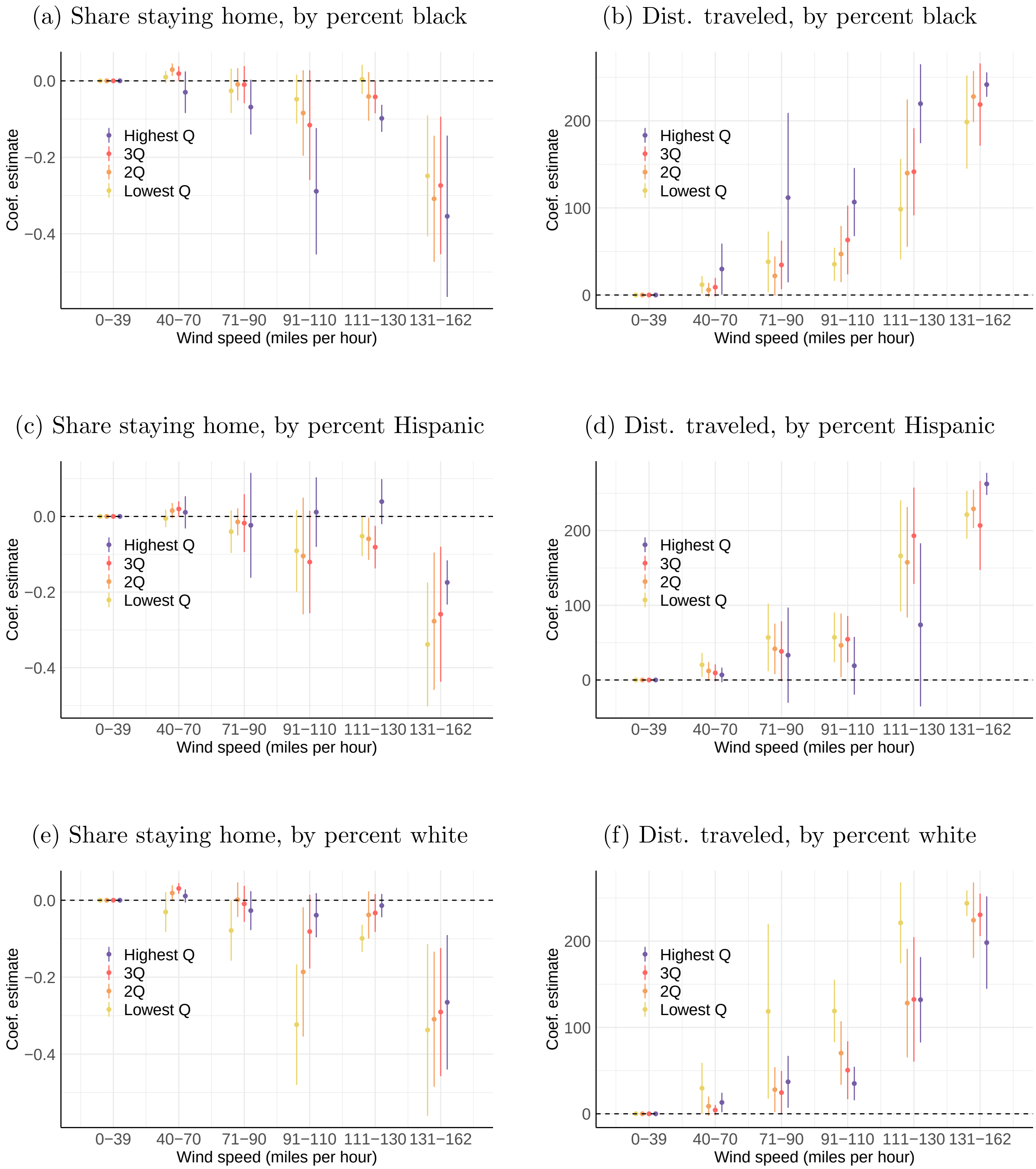


(f) Dist. traveled, het. by urbanicity



Notes: Total effects from estimating Equation 2, interacting hurricane indicators and evacuation orders with quantiles of demographic variables. Demographic heterogeneity is measured by quartile for education and income, while urbanicity takes an indicator equal to one if the block group had greater than 50 percent population that is urban. Standard errors for the combined effects are computed using the delta method.

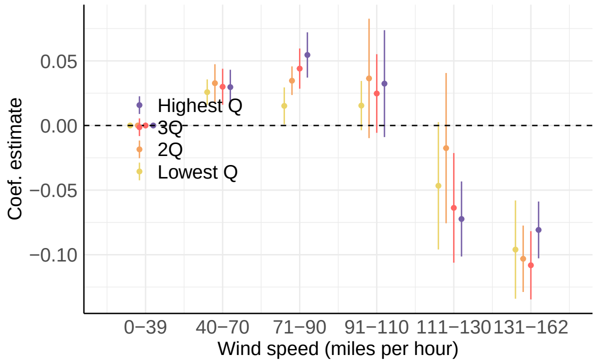
Figure C2: Responses to mandatory evacuation orders by race



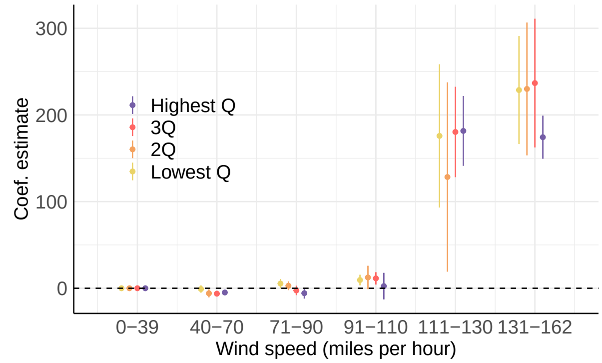
Notes: Total effects from estimating Equation 2, interacting hurricane indicators and evacuation orders with quantiles of demographic variables. Demographic heterogeneity is measured by quartile based on the percent of a block group that is black, Hispanic, or non-white. Standard errors for the combined effects are computed using the delta method.

Figure C3: Responses to voluntary evacuation orders by education, income, and urbanicity

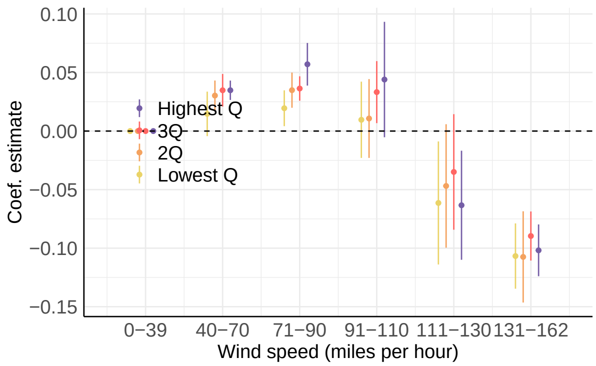
(a) Share staying home, het. by education



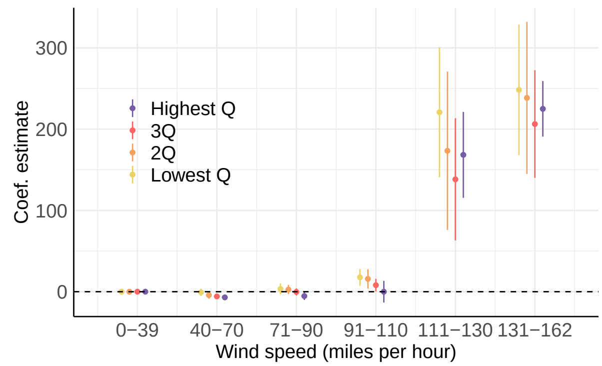
(b) Dist. traveled, het. by education



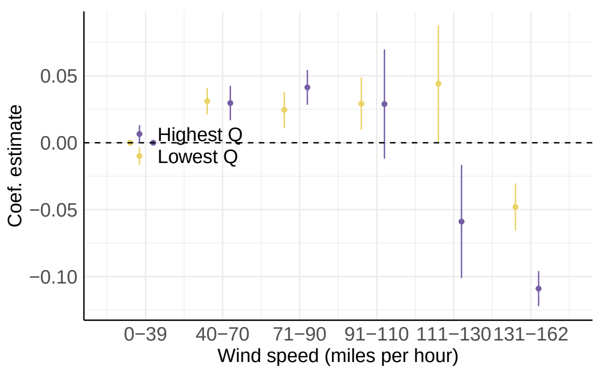
(c) Share staying home, het. by income



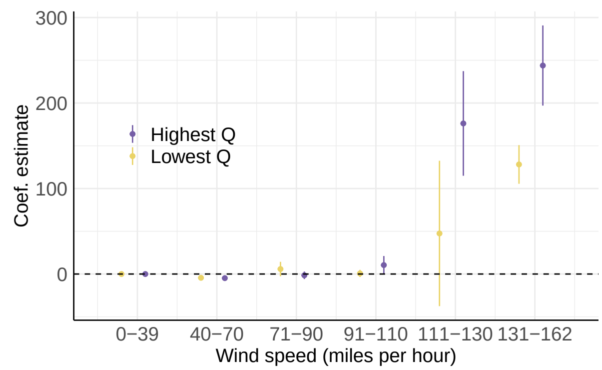
(d) Dist. traveled, het. by income



(e) Share staying home, het. by urbanicity



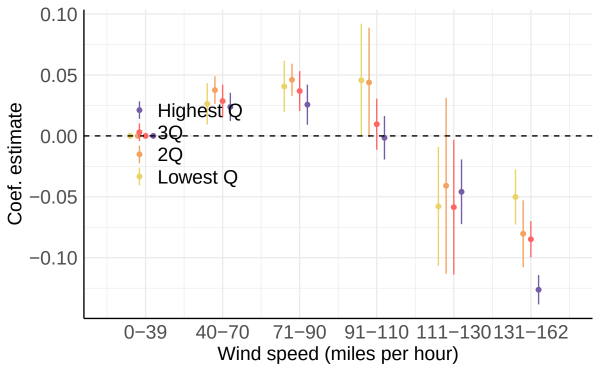
(f) Dist. traveled, het. by urbanicity



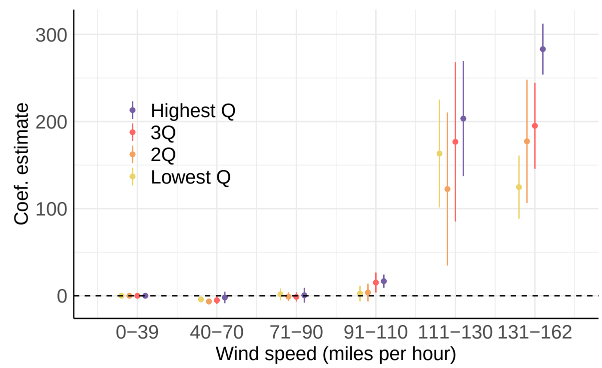
Notes: Total effects from estimating Equation 2, interacting hurricane indicators and evacuation orders with quantiles of demographic variables. Demographic heterogeneity is measured by quartile for education and income, while urbanicity takes an indicator equal to one if the block group had greater than 50 percent population that is urban. Standard errors for the combined effects are computed using the delta method.

Figure C4: Responses to voluntary evacuation orders by race

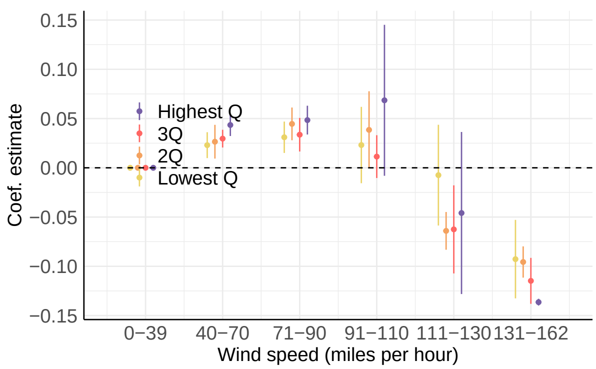
(a) Share staying home, by percent black



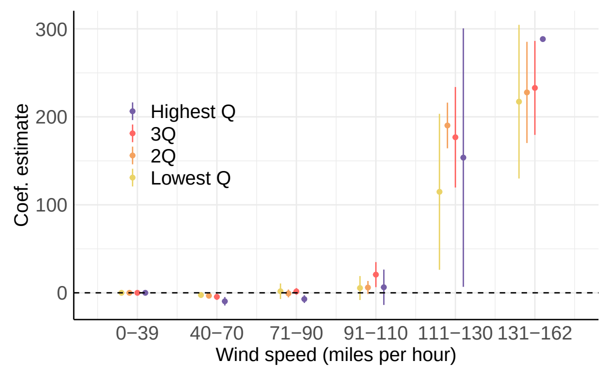
(b) Dist. traveled, by percent black



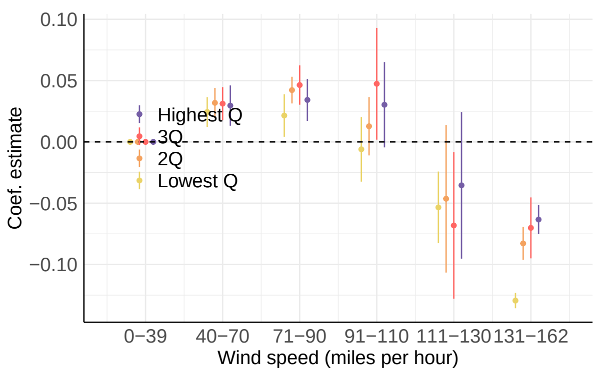
(c) Share staying home, by percent Hispanic



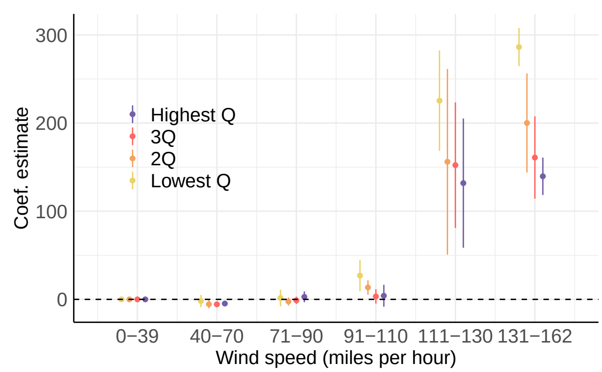
(d) Dist. traveled, by percent Hispanic



(e) Share staying home, by percent white



(f) Dist. traveled, by percent white



Notes: Total effects from estimating Equation 2, interacting hurricane indicators and evacuation orders with quantiles of demographic variables. Demographic heterogeneity is measured by quartile based on the percent of a block group that is black, Hispanic, or non-white. Standard errors for the combined effects are computed using the delta method.

Appendix D: Dynamic Effects of Hurricanes

The main analysis assumes purely contemporaneous effects of hurricanes on movement behavior. This appendix assesses the plausibility of this assumption by exploring dynamic effects of hurricanes on movement. Our empirical test re-estimates the reduced form regressions of Section 3 in a distributed lag structure (Schmidheiny and Siegloch 2023).

We make several modifications for the dynamic regression. For parsimony, we omit evacuation order indicators. In addition, we distinguish severity only by whether a storm was Category 3 or greater, giving wind speed bins $b \in \{40\text{-}110,\ 110+\}$. The panel includes only the months of June through November, which shortens the potential effect window. We consider leads of $d = -4$ weeks and lags of $d = 12$ weeks, with endpoints binned for exposure beyond the effect window but within the same season. With a balanced panel, we estimate:

$$y_{zt} = \sum_{d=-4}^{12} \sum_{b \in B} \psi_{bd} \cdot H^{b}_{z(t-d)} + \delta_z + \lambda_t + \epsilon_{zt}, \tag{15}$$

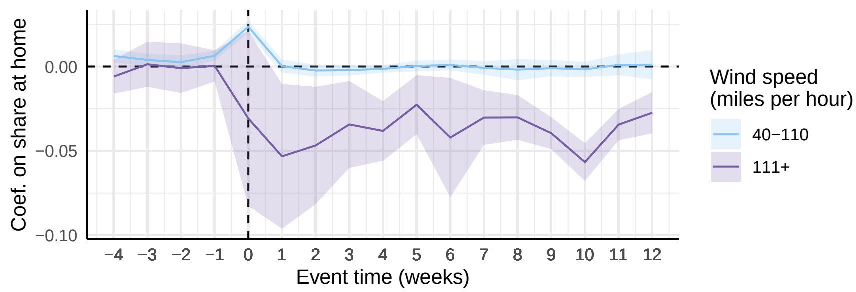
with $y_{zt} \in \{s^0_{zt},\ dist^{75}_{zt},\ \log(visits_{zt})\}$. The coefficients of interest are the ψ_{bd} parameters for each wind speed bin and event lag. We do not normalize any coefficient to zero; the reference category is block groups that did not experience a storm in a given season, since they carry a value $H_{z(t-d)} = 0$ for all periods in the season. For regressions involving foot traffic, we again include the term $(1 - h_{zt})d^{-1}_{zt}$ to control for spillovers, as in Equation 3. We weight regressions by block group population and cluster standard errors at the county level.

Figure D1 displays results. For mild storms, movement activity quickly returns to baseline levels after one week. On the other hand, effects for stronger hurricanes persist for several weeks. Although distance traveled returns to baseline, the share staying in their home county and total foot traffic are both significantly different for the entire feasible effect size window. These patterns could speak either to individuals taking extended stays outside their home county, or to post-disaster recovery and rebuilding activity (Roth Tran and Wilson 2025).

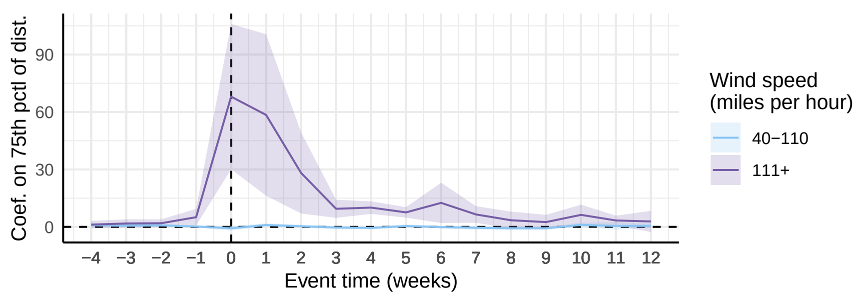
The dynamic effects we observe are not easily accommodated into a travel cost demand model. In a discrete choice framework, individuals make a single choice each period, attributing the full travel cost of a trip as the “price” of the chosen alternative. In our setting, we cannot rule out that individuals stay outside their home county longer than one period, in which case lag structures in utility would overstate welfare costs by attributing one extended stay to multiple full trips. Alternatively, if increased activity is due to rebuilding, it would not constitute an evacuation. We therefore elect to omit dynamic effects from the main analysis. We consider this modeling choice to be conservative.

Figure D1: Event study plots for evacuation, sheltering, and foot traffic

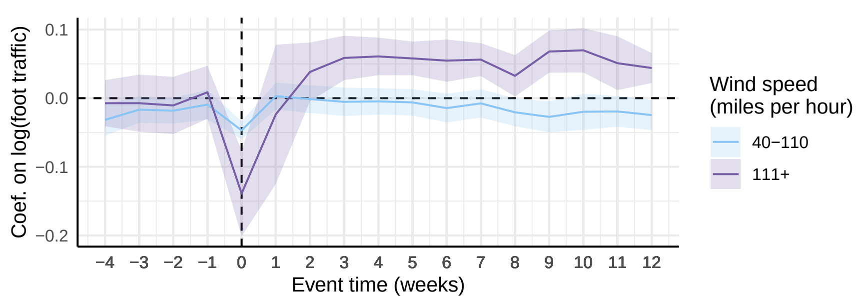
(a) Share staying in home area



(b) The 75th percentile of distance traveled



(c) Foot traffic



Notes: Distributed lag results following Equation 15. For mild to moderate storms, movement activity returns to baseline levels after one week. For severe hurricanes, effects persist for several weeks. Weights are by block group population. Standard errors are clustered at the county level.

Appendix E: Zero Market Shares

In this appendix we explore the implications of zero market shares for the structural estimation of Section 4. As discussed in the main text, ignoring zero market shares attenuates demand parameters by excluding rejected choice alternatives (Gandhi, Lu, and Shi 2023; Li 2023). This insight was studied in a recreation setting by Cheng and Wan (2026), who showed that excluding zero market shares can particularly bias the travel cost coefficient.

To demonstrate these mechanisms in our setting, we report regression results when excluding zero market shares. Specifically, we re-estimate Equation 14 using the observed shares s_{zjt} rather than the Bayesian posterior mean shares $\hat{s}_{zjt}$. By dropping the zeros, the estimation includes only 52.6 million observations.

Table E1 reports results. This table can be directly compared to the main results of Table A2. As expected, demand parameters are attenuated in the selected sample relative to the full sample. To see the effect on welfare estimates, Table E2 reports WTP values when ignoring zero market shares. These estimates can be much higher due to the attenuated travel cost parameter. For example, WTP is computed at \$409 per person under Category 4 and 5 winds and under mandatory evacuation order, compared to \$343 per person when accounting for zero market shares. Sheltering costs can be as high as \$55 per person when ignoring zeros, compared to \$14 to \$24 in the main analysis.

These differences raise the question of whether the Bayesian shrinkage estimator actually induces bias by upward-adjusting low movement shares during sheltering events and downward-adjusting high movement shares during evacuation events. To assess this possibility, we regress the difference between the Bayesian posterior mean share and the observed share, $(\hat{s}_{zjt} - s_{zjt})$, on hurricane and evacuation order indicators.

Table E3 reports results from the estimation. We find values very close to zero in most cases. To contextualize the estimates, the largest magnitude coefficient is approximately 0.0022, which, when compared to the travel cost coefficient of -0.005 in the main estimation, would result in an additional \$0.44 added to the welfare cost of Category 4 and 5 hurricanes under mandatory evacuation orders. As the total estimated effect is approximately \$343 per person, we consider this exercise to be evidence against potential shrinkage bias.

Table E1: Structural estimation ignoring zero market shares

	(1)	(2)
Travel cost (dollars)	-0.003***	-0.003***
	(0.0001)	(0.0001)
Storm path (dest.)	-0.033***	-0.035***
	(0.004)	(0.005)
Storm path (orig.) × Storm path (dest.) × Wind spd diff.	0.0001	0.0001
	(0.0001)	(0.0001)
Storm path (orig.) × Wind spd 40-70	-0.069***	-0.066***
	(0.005)	(0.006)
Storm path (orig.) × Wind spd 71-90	-0.098***	-0.075***
	(0.018)	(0.024)
Storm path (orig.) × Wind spd 91-110	-0.090***	0.077
	(0.033)	(0.074)
Storm path (orig.) × Wind spd 111-130	-0.150*	-0.250***
	(0.081)	(0.053)
Storm path (orig.) × Wind spd 131-162	0.211***	0.190**
	(0.074)	(0.080)
Storm path (orig.) × Wind spd 40-70 × Vol. evac. order	-0.084***	
	(0.022)	
Storm path (orig.) × Wind spd 71-90 × Vol. evac. order	-0.004	
	(0.032)	
Storm path (orig.) × Wind spd 91-110 × Vol. evac. order	0.038	
	(0.051)	
Storm path (orig.) × Wind spd 111-130 × Vol. evac. order	0.387***	
	(0.118)	
Storm path (orig.) × Wind spd 131-162 × Vol. evac. order	0.139	
	(0.123)	
Storm path (orig.) × Wind spd 40-70 × Man. evac. order	0.032	
	(0.045)	
Storm path (orig.) × Wind spd 71-90 × Man. evac. order	0.308**	
	(0.120)	
Storm path (orig.) × Wind spd 91-110 × Man. evac. order	0.399***	
	(0.150)	
Storm path (orig.) × Wind spd 111-130 × Man. evac. order	0.386**	
	(0.157)	
Storm path (orig.) × Wind spd 131-162 × Man. evac. order	0.939***	
	(0.328)	
Storm path (orig.) × Wind spd 40-70 × NWS alert		-0.018
		(0.022)
Storm path (orig.) × Wind spd 71-90 × NWS alert		0.070
		(0.053)
Storm path (orig.) × Wind spd 111-130 × NWS alert		0.411***
		(0.108)
Storm path (orig.) × Wind spd 131-162 × NWS alert		0.733**
		(0.328)
Block group orig. FE	Yes	Yes
County dest. FE	Yes	Yes
Week-year FE	Yes	Yes
N	52,583,430	52,583,430

Notes: Regression for structural estimation when dropping zero market shares. This table can be directly compared to the main results of Table A2. Wind speed is reported in miles per hour. 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. The dependent variable is $\log(s_{zjt}) - \log(s_{z0t})$. 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. WTP estimates when dropping zero market shares are reported in Table E2, which in turn can be compared to Table A3. General coefficient standard errors are clustered by origin county. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E2: Summary of WTP estimates ignoring zero market shares

Wind speed	No order	Voluntary order	NWS alert	Mandatory order
40-70	-24.68***	-54.59***	-30.18***	-13.24
	(1.86)	(8.09)	(8.25)	(16.39)
71-90	-34.84***	-36.32***	-1.88	74.87*
	(6.07)	(9.70)	(17.97)	(42.97)
91-110	-31.95***	-18.44		110.05**
	(11.73)	(14.69)		(51.86)
111-130	-53.54*	84.31***	57.16*	83.98*
	(28.68)	(32.36)	(33.16)	(47.46)
131-162	74.94***	124.28***	328.51***	409.11***
	(26.57)	(37.74)	(112.96)	(113.92)

Notes: Summary of WTP estimates when ignoring zero market shares, corresponding to Table E1. For WTP estimates in the main analysis, compare to Table A3. 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E3: Regression to assess potential shrinkage bias

	(1)
Travel cost (dollars)	-0.000007***
	(0.0000005)
Storm path (dest.)	0.000067***
	(0.000020)
Storm path (orig.) × Storm path (dest.) × Wind spd diff.	0.000003**
	(0.000001)
Storm path (orig.) × Wind spd 40-70	0.000131***
	(0.000044)
Storm path (orig.) × Wind spd 71-90	-0.000187**
	(0.000093)
Storm path (orig.) × Wind spd 91-110	0.000070
	(0.000184)
Storm path (orig.) × Wind spd 111-130	0.000336*
	(0.000176)
Storm path (orig.) × Wind spd 131-162	-0.002000***
	(0.000236)
Storm path (orig.) × Wind spd 40-70 × Vol. evac. order	0.000393*
	(0.000207)
Storm path (orig.) × Wind spd 71-90 × Vol. evac. order	-0.000167
	(0.000184)
Storm path (orig.) × Wind spd 91-110 × Vol. evac. order	-0.000091
	(0.000241)
Storm path (orig.) × Wind spd 111-130 × Vol. evac. order	-0.000289
	(0.000225)
Storm path (orig.) × Wind spd 131-162 × Vol. evac. order	0.001970***
	(0.000312)
Storm path (orig.) × Wind spd 40-70 × Man. evac. order	-0.000093
	(0.000183)
Storm path (orig.) × Wind spd 71-90 × Man. evac. order	-0.000305
	(0.000297)
Storm path (orig.) × Wind spd 91-110 × Man. evac. order	-0.000563*
	(0.000326)
Storm path (orig.) × Wind spd 111-130 × Man. evac. order	-0.002377*
	(0.001389)
Storm path (orig.) × Wind spd 131-162 × Man. evac. order	0.002217***
	(0.000566)
Block group orig. FE	Yes
County dest. FE	Yes
Week-year FE	Yes
N	52,591,004

Notes: Regression of the difference between the Bayesian posterior mean share and the observed movement share, $(\hat{s}_{zjt} - s_{zjt})$, on hurricane and evacuation order indicators. Standard errors are clustered by county. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.