

Household Evacuation Planning and Preparation for Future Hurricanes: Role of Utility Service Disruptions

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Abstract

We analyzed data from a survey administered to 1,212 respondents living in superstorm Hurricane Sandy-affected areas. We estimated the effect of having experienced hurricane-induced disruptions to utility services, such as electricity, water, gas, phone service, and public transportation, on having an evacuation plan. Around 39% of respondents reported having an evacuation plan in case a hurricane affects their neighborhood this year. Respondents who had experienced disruptions to electricity supply had an approximately 11 percentage-point higher likelihood of having an evacuation plan than those who had experienced no such disruptions. Respondents who had experienced monetary losses from Hurricane Sandy had around a five percentage-point higher likelihood of having an evacuation plan compared with those who had not. Among control variables, prior evacuation, distance to the coastline, residence in a flood zone, concern about the impacts of future natural disaster events, had window protection, and household members being disabled, each had an association with residents' future evacuation planning and hurricane preparedness. In light of these findings, we discuss the policy implications of our findings for improving disaster management in hurricane-prone areas.

In the United States, the toll from natural disasters is skyrocketing, with rising trends in the rates of property damage and human suffering. Between 1980 and 2019 in the United States, damage from weather and climate-related disasters was estimated to be \$1.75 trillion, approximately \$550 billion of which can be attributed to the disasters of the past 3 years (1). Hurricanes are the costliest of all forms of natural disaster (2–4). Since 1980, the top 10 costliest natural disasters include seven hurricanes, including Hurricane Harvey and Hurricane Irma (5). Evacuation during a hurricane has the potential to reduce human suffering by reducing vulnerabilities to physical injury, trauma, or death among evacuees (6–9). However, evacuation rates remain low among hurricane-affected area residents, creating a hurricane risk-management challenge (10–12).

In this paper, we examine the role of experiencing utility service disruptions in a prior hurricane event on evacuation planning for a future hurricane. Most prior research has overlooked past utility disruptions as a predictor of future evacuations, although significant inroads have been made in identifying who are at risk of remaining at home during a hurricane and why (13). Lack of knowledge about the role of past utility disruptions on

future evacuations leaves not only a gap in the literature but represents a missed opportunity to develop more targeted and tailored risk communication strategies if past utility disruption is indeed a key predictor.

We argue that individuals who have experienced disruptions in utility service delivery into their homes and communities during, after, or both during and after a hurricane event will be more motivated to evacuate during a future hurricane event, compared with individuals with no such experience. Disruptions in utility services, including electricity, water, sanitation, transportation, and communication services, can cause fatalities, social

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isolation, and disruptions to daily social and economic activities (14, 15). Power outages can cause disruptions in delivering essential services, including heating, lighting, and the use of elevators, potentially causing death and injury (16). Power outages can also result in people suffering minor illnesses from consumption of contaminated food or water (17). Further, people may have restricted access to emergency and social services if experiencing utility service disruptions post-disaster (18). Finally, people may fail to receive service loss and restoration updates if experiencing disruptions in communication systems, which are increasingly being used for community alerts (19, 20).

We conducted a model-building exercise coupled with spatial analysis. By employing a probit regression model, we estimated the effect of prior experience of disruptions in relation to each of five utility types on the likelihood of evacuation planning, using data collected via an original web-based survey of 1,212 residents living in Hurricane Sandy-affected areas in 2013. Furthermore, we performed a spatial analysis using ArcGIS (Esri, Redlands, CA). We also developed a spatial probit model for robustness checks. We found disruptions in electricity in a prior hurricane event increased the likelihood of evacuation planning for a future hurricane. Our findings have the potential to inform evacuation preparedness and planning policies for mitigating coastal hazard risks.

Literature Review

Preparedness refers to the preparing of equipment and procedures (21). Planning refers to mitigating the results and effects of any emergencies (22–24). In the context of a hurricane, both preparedness and planning are complex behaviors associated with multidimensional factors, including risk perceptions, income, ethnicity, and education levels (25). Several demographic and household factors are associated with hurricane evacuation decisions: gender, family size, whether there are children in the household, and having a pet (26–29). Prior experience of a hurricane has been identified as a determinant in certain studies but not in others (30, 31). Spatial characteristics are also important predictors of evacuation decisions. Solís et al. found that living in vulnerable areas (i.e., living in a flood zone, mobile home) increases the probability of evacuation (32). Furthermore, people living in southeast Florida were less likely to evacuate than those living in northwest Florida (33).

To date, we know very little about the role of utility disruptions during hurricanes in relation to evacuation. Literature on utility disruptions has explored effects in relation to psychosocial and economic factors. Chatterjee and Mozumder found that family wellbeing was significantly affected by disruptions in public utility services

(e.g., water supply, electricity, and telephone) and the suspension of local economic activities (e.g., transportation and local businesses) during Hurricane Wilma (34). Mayer et al. found that an estimated 57% of businesses in affected areas experienced power outages during Hurricane Rita, and 85% of the businesses experienced loss of electricity had to remain closed as a result (35). Furthermore, they found that this power loss was even more damaging to the businesses than employees who were absent because of the hurricane (57.7%) or the lack of customers (30.9%). Carlsson et al. found that a significant driver of post-hurricane stress has often been the disruption in utility services (electricity, water supply, and telecommunications) (36). Post-hurricane stress can be a major driver of future evacuation decisions (37, 38). To fill in the gap in prior literature, we examined the role of past utility disruptions on future evaluation planning. We believe that understanding the role of utility disruptions could help to develop more targeted and tailored risk communication strategies and help guide communities to a quick recovery after a hurricane.

Methods

Survey Design

In July 2013, researchers at the Social Science Laboratory of the International Hurricane Research Center at Florida International University conducted a cross-sectional, web-based survey of households living in one of nine states (New Jersey [NJ], New York [NY], Connecticut [CT], Maryland [MD], Massachusetts [MA], Virginia [VA], Delaware [DE], Pennsylvania [PA], and Rhode Island [RI]) affected by the superstorm Hurricane Sandy in 2012. Respondents were selected randomly from eligible adult (18 years of age or older) households from KnowledgePanel, a probability-based web panel designed to be representative of the United States (39). The survey asks questions about household experiences during the hurricane, including evacuation decisions, days of utility disruptions experienced, and property damage. Information on evacuation planning and preparation for future hurricanes and sociodemographic characteristics is also collected. The survey was attempted by 3,276 adults; among those, 2,028 completed the survey, giving a 61.93% completion rate; among those, 1,212 were identified as qualified responses, providing a qualification rate of 59.76%. Survey completion time ranged between 15 and 20 min. Data collection occurred during July 7 to 22, 2013.

Measures

Dependent Variables. We measured disaster preparedness as a binary variable for which households were assigned

the value of 1 if they answered “yes” to Have you made the necessary preparations to leave your home to go someplace safer in the event of a hurricane this year? or Does your household have an evacuation plan in case a hurricane hits your neighborhood this year? The household was assigned zero otherwise.

Explanatory Variables. We measured utility disruptions as a binary variable for households having experienced disruptions to electricity, water, gas, phone/cell phone, and public transportation services during Hurricane Sandy. For example, households were assigned the value of 1 if they had experienced electricity disruptions for at least 1 day; they were assigned a zero otherwise. We followed the same approach for measuring disruptions to water, gas, phone/cell phone, and public transportation services. We preferred binary to continuous measures as 90% of the households had experienced disruptions of up to 7 days to water, gas, phone, and public transportation services, and 75% had experienced up to 7 days’ disruption to electricity services.

Control Variables. We considered a total of 29 variables grouped into (a) sociodemographic (household size; the number of disabled members in the household; the number of elderly members in the household; the number of pets; respondent’s gender, race, age, and household head status; and household state of residence); (b) education, income, and behavioral correlates (i.e., respondent’s highest level of education attained; household income measured with an ordinal scale; respondent’s risk perception measured as a respondent rating of his/her level of concern about the impacts of future natural disasters; whether the household had flood insurance; and whether household had window protection); (c) natural and built environment (i.e., household residing in a flood zone; the age of the housing structure); (d) prior disaster and evacuation experiences (i.e., household evacuated during Hurricane Sandy; household incurring monetary damages during Hurricane Sandy); (e) spatial correlates (i.e., respondent’s nearest distance to the coastline in miles); and (f) state of residence (a dummy variable indicating a respondent’s state of residence as NJ, NY, CT, MD, MA, VA, DE, PA, or RI). We measured the control variables as a dummy or continuous variable.

Estimation Strategy

Using a probit model, we tested whether households who had experienced utility service disruptions resulting from a disaster event in the past were more likely to be prepared for a potential hurricane event in the future. We estimated the following equation:

$$\Phi^{-1}(Y) = X\beta + \varepsilon.$$

where Y denotes disaster preparedness, and X denotes a vector of explanatory and control variables and state dummy variables. We estimated the equation using a probit model, as appropriate for the level of measurement for the dependent variable, with robust standard errors (ε). The Φ represents the cumulative standard normal distribution for a probit model and β represent the conformable vector of relevant coefficients to be estimated.

We estimated a total of five models. First, we estimated a baseline model using the explanatory variables of household evacuations during Hurricane Sandy and any monetary loss incurred. We extended this baseline model by sequentially adding utility disruption variables: education, income, and behavioral correlates; spatial correlates; natural and built environment variables; and sociodemographic variables.

Before model estimations, we conducted a descriptive analysis to assess variable completeness and distributional properties. There was little missing or invalid data on control variables, generally around 1%, which were handled by imputing the mean (for continuous variables) or mode (for categorical variables). Bivariate analyses of the explanatory and control variables did not indicate collinearity, with the highest correlation between any two covariates being 0.39.

For the robustness checks, we reiterated the analysis using logit models (see Table A1 in the Appendix).

Furthermore, we performed a spatial analysis using ArcGIS. Initially, this was based on three questions: Did you evacuate during Hurricane Sandy? Do you have an evacuation plan for future hurricanes? Does your household have an evacuation plan in case a hurricane hits your neighborhood this year? We grouped the households into four categories: (1) evacuees with no planning/preparation (evacuation = 1, planning/preparation = 0); (2) evacuees with planning/preparation (evacuation = 1, planning/preparation = 1); (3) non-evacuees with no planning/preparation (evacuation = 0, planning/preparation = 0); and (4) non-evacuees with planning/preparation (evacuation = 0, planning/preparation = 1). We produced four maps, corresponding to the four groups, to show group-specific geocoded locations and the effects of utility disruptions on future evacuation planning and preparation. We subsequently used a geographic information system (GIS) to generate an additional control variable: distance to the coastline. The Hazards U.S. Multi-Hazard (HAZUS-MH) software (Federal Emergency Management Agency, Washington, D.C.) was utilized to generate Hurricane Sandy’s wind track and to estimate wind speed at the census-tract level, to provide a visual presentation of Sandy-affected areas and to demonstrate the representativeness of our sample.

Table 1. Description of Variables Used and Descriptive Statistics, *N* = 1,212

Variables	Proportion/mean	SD
Self or family has a plan to evacuate in a future hurricane event	0.39	0.49
Household experienced monetary damages during Hurricane Sandy	0.35	0.48
Evacuated when affected by Hurricane Sandy	0.08	0.27
Electricity was interrupted for at least 1 day	0.73	0.44
Water supply was interrupted for at least 1 day	0.16	0.37
Gas was interrupted for at least 1 day	0.19	0.39
Phone/cell phone was interrupted for at least 1 day	0.49	0.50
Public transportation interrupted for at least 1 day	0.38	0.49
Respondent's highest level of education: some college	0.28	0.45
Respondent's highest level of education: bachelor's degree or higher	0.58	0.49
Household income (measured on an interval scale)	13.15	4.15
Respondent is concerned about the impacts of future natural disaster events	0.57	0.50
Has a flood insurance	0.07	0.27
Household has window protection	0.14	0.35
Lives in a flood zone	0.13	0.34
Household age	52.65	31.72
Household size	2.49	1.28
Number of disabled members in household	0.19	0.52
Number of elderly members in household	0.49	0.75
Number of pets owned	1.07	1.68
Respondent is female	0.60	0.49
Respondent is white	0.80	0.40
Respondent is Hispanic	0.07	0.26
Respondent is of mixed race	0.02	0.14
Respondent is a member of other races	0.03	0.17
Respondent's age	52.91	15.43
Respondent is the household head	0.87	0.34
Respondent's nearest distance to the coastline in miles	6.48	8.87
State of residence: MA or RI	0.06	0.23
State of residence: NY	0.29	0.46
State of residence: CT	0.12	0.32
State of residence: NJ	0.35	0.48
State of residence: PA	0.07	0.25
State of residence: DE, MD, or VA	0.11	0.31

Note: SD = standard deviation.

Results

Descriptive Statistics

Table 1 presents descriptive statistics. The majority of respondents were female (60%), white (80%), household heads (87%), and had at least a bachelor's degree (58%). On average, respondents were 53 years old, living in households with three members, one disabled member, one elderly member, and one pet. About 13% of respondents were living in a flood zone; 7% had flood insurance; 14% had window protections in their households; and 57% reported concerns about the impact of future natural disaster events.

Less than half (39%) the respondents reported making necessary preparations in the event of a hurricane or that they had an evacuation plan for themselves and their families. Only 8% of respondents reported that they had evacuated during Hurricane Sandy, although four

times as many (35%) reported experiencing monetary loss owing to the hurricane.

Figure 1 shows the distribution of hurricane preparedness and evacuation planning among respondents by state. With the exception of the respondents from PA, those from all other states reported evacuation planning more frequently than they reported overall disaster preparedness. VA showed a more significant gap: more than 60% of respondents had an evacuation plan but less than 40% of them had made necessary preparations. People who have an evacuation plan usually do not need out-of-pocket expenses, however, people who undertake disaster preparedness may need to spend time and money on storing supplies, securing their home, or purchasing hurricane preparedness kits (includes water, food, flashlight, battery-powered radio, extra batteries, medications, and cell phone with charger, etc.).

The percent affected by service disruptions for at least 1 day varied across service types: electricity (73%);

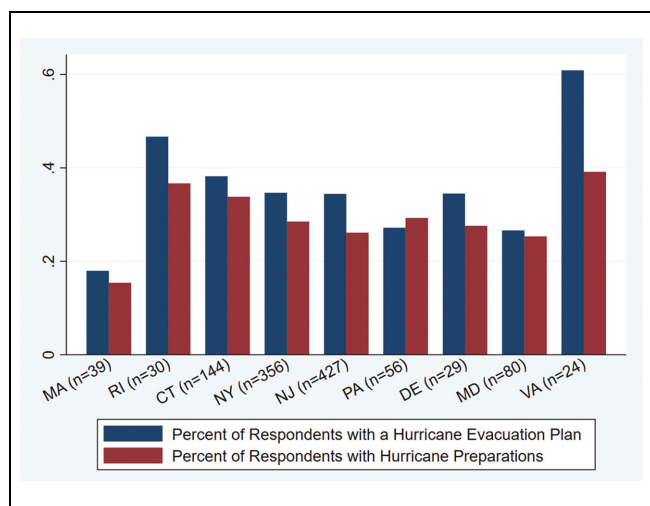


Figure 1. Percent of respondents with hurricane preparation and evacuation planning by state.

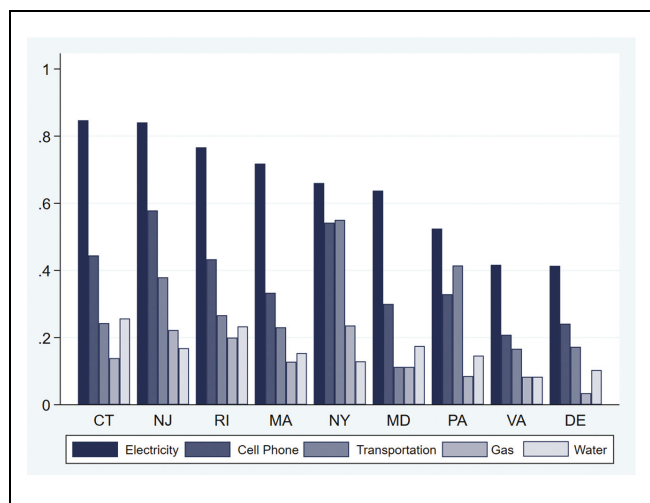


Figure 2. Percent of respondents experiencing service disruptions (by service type and state).

phone/cell phone (49%); public transportation (38%); water (16%); and gas (19%). Figure 2 displays the percentage of respondents by each type of utility disruption across different states.

Table 2 presents the probit estimates for future evacuation planning, and Table 3 reports the marginal effects. In Table 3, Model 1 reports the marginal effect of prior evacuation experience, an established predictor of evacuation preparedness, along with the utility disruption variables. Model 2 extends Model 1 by adding education-related variables and income. Model 3 includes the spatial correlates (i.e., respondent's nearest distance to the coastline in miles). Model 4 adjusts for behavioral

correlates: state of residence and environmental control. Model 5 extends Model 4 by adding sociodemographic-related controls. To check the robustness of our models, we also tested logit models, which returned similar significant coefficients levels as the probit model estimations (see Table A1 in the Appendix).

Model 1 in Table 3 indicates that prior evacuation experiences matter for evacuation preparedness. Respondents who had evacuated during Hurricane Sandy had a 29 percentage-point higher likelihood of having an evacuation plan compared with those who had not (dy/dx: 0.294, significance at 1%; Model 1). Further, respondents who had experienced monetary loss as a result of Hurricane Sandy had a five percentage-point higher likelihood of having an evacuation plan than those who had not experienced such loss (dy/dx: 0.052, significance at 1%; Model 1). Interestingly, respondents who experienced electricity disruptions had a 10 percentage-point higher likelihood of having an evacuation plan compared with those who had experienced no such disruptions (dy/dx: 0.102, significance at 1%; Model 1). This association was robust to the inclusion of prior experiences of evacuation and monetary loss resulting from Hurricane Sandy.

The positive association between prior experience of electricity disruptions and evacuation preparedness was robust to the further inclusion of a range of control variables, including prior evacuation and monetary loss (Model 1); the highest level of education attained and income (Model 2) and spatial variable (Model 3); behavioral factors (i.e., having flood insurance or window protection) (Model 4); environmental factors including living in a flood zone, the age of the house, and the states of residence (Model 4), and sociodemographic variables (Model 5).

Among the controls in the full model (Model 4), disabled household members (dy/dx: 0.057, significance at 5%), household has window protection (dy/dx: 0.084, significance at 5%), living in a flood zone (dy/dx: 0.108, significance at 5%), concerns about the impacts of future disaster events (dy/dx: 0.056, significance at 5%), and prior evacuation (dy/dx: 0.235, significance at 1%) each had a positive association with having an evacuation plan. In relation to associations between spatial distance and having an evacuation plan, respondents had a 0.3% higher likelihood of evacuating if they lived 1 mi closer to the coastline (dy/dx: -0.003, significance at 5%; Model 3).

GIS-Based Further Disaggregated Analysis

Figures 3 and 4 present the locations of each of the four groups (evacuees with no planning/preparation, evacuees with planning/preparation, non-evacuees with no

Table 2. Probit Model Estimates for Future Hurricane Planning

Dependent variable: self or family has a plan to evacuate in a future hurricane event

	Model 1	Model 2	Model 3	Model 4	Model 5
Disaster experience: utility disruptions and other damages					
Household experienced any monetary damages during the Hurricane Sandy	0.141* (0.081)	0.142* (0.082)	0.136* (0.082)	0.138* (0.084)	0.142* (0.085)
Evacuated when affected by Hurricane Sandy	0.795*** (0.145)	0.790*** (0.145)	0.764*** (0.146)	0.643*** (0.153)	0.655*** (0.154)
Electricity was interrupted for at least 1 day	0.275*** (0.099)	0.288*** (0.100)	0.303*** (0.100)	0.294*** (0.103)	0.325*** (0.104)
Water supply was interrupted for at least 1 day	−0.133 (0.111)	−0.136 (0.111)	−0.119 (0.112)	−0.160 (0.116)	−0.170 (0.117)
Gas was interrupted for at least 1 day	0.036 (0.104)	0.033 (0.105)	0.025 (0.104)	0.014 (0.107)	0.030 (0.108)
Phone/cell phone was interrupted for at least 1 day	0.026 (0.086)	0.021 (0.086)	0.022 (0.086)	0.018 (0.088)	0.013 (0.088)
Public transportation interrupted for at least 1 day	−0.051 (0.079)	−0.052 (0.080)	−0.069 (0.080)	−0.055 (0.083)	−0.055 (0.085)
Education and income					
Respondent's highest level of education: Some college	NA	0.050 (0.123)	0.038 (0.123)	0.002 (0.124)	−0.004 (0.126)
Respondent's highest level of education: bachelor's degree or higher	NA	0.017 (0.117)	0.023 (0.117)	−0.027 (0.119)	−0.049 (0.121)
Household income (measured in an interval scale)	NA	−0.008 (0.010)	−0.008 (0.010)	−0.007 (0.010)	−0.002 (0.010)
Spatial correlates					
Respondent's nearest distance to the coastline in miles	NA	NA	−0.009** (0.004)	NA	NA
Behavioral correlates and environmental control					
Respondent is concerned about the impacts of future natural disaster events	NA	NA	NA	0.154** (0.078)	0.155** (0.079)
Has a flood insurance	NA	NA	NA	0.179 (0.159)	0.228 (0.162)
Household has a window protection	NA	NA	NA	0.249** (0.111)	0.236** (0.112)
Lives in a flood zone	NA	NA	NA	0.330*** (0.123)	0.302** (0.125)
Household age	NA	NA	NA	−0.000 (0.001)	−0.001 (0.001)
State of residence					
State of residence: MA/RI	NA	NA	NA	−0.239 (0.199)	−0.267 (0.200)
State of residence: NY	NA	NA	NA	−0.117 (0.141)	−0.141 (0.142)
State of residence: CT	NA	NA	NA	0.044 (0.160)	0.028 (0.162)
State of residence: NJ	NA	NA	NA	−0.198 (0.137)	−0.229* (0.139)
State of residence: PA	NA	NA	NA	−0.177 (0.184)	−0.169 (0.187)
Sociodemographic correlates					
Household size	NA	NA	NA	NA	−0.051 (0.034)
Number of disabled members in household	NA	NA	NA	NA	0.159** (0.076)
Number of elderly members in household	NA	NA	NA	NA	−0.077 (0.064)
Number of pets owned	NA	NA	NA	NA	0.003 (0.022)
Respondent is female	NA	NA	NA	NA	−0.075 (0.079)
Respondent is white	NA	NA	NA	NA	0.146 (0.156)
Respondent is Hispanic	NA	NA	NA	NA	0.254 (0.202)
Respondent is of mixed race	NA	NA	NA	NA	0.392 (0.291)
Respondent is a member of other races	NA	NA	NA	NA	0.285 (0.273)
Respondent's age	NA	NA	NA	NA	0.001 (0.003)
Respondent is the household head	NA	NA	NA	NA	0.173 (0.121)
Constant	−0.569*** (0.079)	−0.492*** (0.154)	−0.434*** (0.157)	−0.484** (0.194)	−0.728** (0.301)
Observations	1,212	1,212	1,212	1,212	1,212

Note: Numbers in parentheses are corresponding standard errors. NA means the variables that are not used in the models.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

planning/preparation, and non-evacuees with planning/preparation).

Figure 3 shows the effect of electricity disruptions on evacuation planning. Among evacuees, 70% of them answered “yes” to evacuation planning or preparing for

future hurricanes, which was associated with a higher percentage of electricity disruption, by 13.49%, and with a higher duration of almost 3 days (see Table 4). One-third of the non-evacuee group (37%) indicated that they now had decided to plan or prepare to evacuate for

Table 3. Analyzing the Role of Utility Service Disruptions on Hurricane Evacuation Planning and Preparation

Dependent variable: self or family has a plan to evacuate in a future hurricane event

	Model 1	Model 2	Model 3	Model 4	Model 5
Disaster experience: utility disruptions and other damages					
Household experienced monetary damages during the Hurricane Sandy	0.052* (0.03)	0.053* (0.03)	0.050* (0.03)	0.050* (0.03)	0.051* (0.03)
Evacuated when affected by Hurricane Sandy	0.294*** (0.052)	0.292*** (0.052)	0.282*** (0.052)	0.233*** (0.054)	0.235*** (0.054)
Electricity was interrupted for at least 1 day	0.102*** (0.036)	0.107*** (0.036)	0.112*** (0.036)	0.106*** (0.037)	0.116*** (0.037)
Water supply was interrupted for at least 1 day	-0.049 (0.041)	-0.050 (0.041)	-0.044 (0.041)	-0.058 (0.042)	-0.061 (0.042)
Gas was interrupted for at least 1 day	0.013 (0.039)	0.012 (0.039)	0.009 (0.039)	0.005 (0.039)	0.011 (0.039)
Phone/cell phone was interrupted for at least 1 day	0.010 (0.032)	0.008 (0.032)	0.008 (0.032)	0.006 (0.032)	0.005 (0.031)
Public transportation interrupted for at least 1 day	-0.019 (0.029)	-0.019 (0.029)	-0.025 (0.03)	-0.020 (0.03)	-0.020 (0.03)
Education and income					
Respondent's highest level of education: some college	NA	0.018 (0.045)	0.014 (0.045)	0.001 (0.045)	-0.001 (0.045)
Respondent's highest level of education: bachelor's degree or higher	NA	0.006 (0.043)	0.008 (0.043)	-0.010 (0.043)	-0.017 (0.043)
Household income (measured in an interval scale)	NA	-0.003 (0.004)	-0.003 (0.004)	-0.003 (0.004)	-0.001 (0.004)
Spatial correlates					
Respondent's nearest distance to the coastline in miles	NA	NA	-0.003** (0.002)	NA	NA
Behavioral correlates and environmental control					
Respondent is concerned about the impacts of future natural disaster events	NA	NA	NA	0.056** (0.028)	0.056** (0.028)
Has a flood insurance	NA	NA	NA	0.065 (0.057)	0.082 (0.058)
Household has a window protection	NA	NA	NA	0.090** (0.04)	0.084** (0.04)
Lives in a flood zone	NA	NA	NA	0.119*** (0.044)	0.108** (0.045)
Household age	NA	NA	NA	0.000 (0)	0.000 (0)
State of residence					
State of residence: MA/RI	NA	NA	NA	-0.086 (0.072)	-0.095 (0.071)
State of residence: NY	NA	NA	NA	-0.042 (0.051)	-0.050 (0.051)
State of residence: CT	NA	NA	NA	0.016 (0.058)	0.010 (0.058)
State of residence: NJ	NA	NA	NA	-0.071 (0.049)	-0.082* (0.05)
State of residence: PA	NA	NA	NA	-0.064 (0.067)	-0.060 (0.067)
Sociodemographic correlates					
Household size	NA	NA	NA	NA	-0.018 (0.012)
Number of disabled members in household	NA	NA	NA	NA	0.057** (0.027)
Number of elderly members in household	NA	NA	NA	NA	-0.028 (0.023)
Number of pets owned	NA	NA	NA	NA	0.001 (0.008)
Respondent is female	NA	NA	NA	NA	-0.027 (0.028)
Respondent is white	NA	NA	NA	NA	0.052 (0.056)
Respondent is Hispanic	NA	NA	NA	NA	0.091 (0.072)
Respondent is of mixed race	NA	NA	NA	NA	0.140 (0.104)
Respondent is a member of other race	NA	NA	NA	NA	0.102 (0.098)
Respondent's age	NA	NA	NA	NA	0.000 (0.001)
Respondent is the household head	NA	NA	NA	NA	0.062 (0.043)
AIC	1,583.195	1,588.083	1,586.168	1,575.996	1,583.644
BIC	1,623.996	1,644.184	1,647.368	1,683.097	1,746.845
LR test	52.88***	54.05***	58.42***	79.04***	92.64***
-2 Log L	-783.598	-783.042	-781.084	-766.998	-759.822
Pseudo R-squared	0.0339	0.0346	0.037	0.0544	0.0632

Note: AIC = Akaike information criterion; BIC = Bayesian information criterion; LR = Likelihood-ratio. Numbers in parentheses are corresponding standard errors. NA means the variables that are not used in the models.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

future hurricanes. Among these non-evacuees, 77.15% had suffered electricity disruption for an average duration of 4.85 days, compared with non-evacuees who said “no” to planning or preparedness (67.64% had experienced electricity disruption for an average of 3.86 days). It is also worth noting that, as shown in Table 4, those

(regardless of evacuee or non-evacuee status) who had planned or prepared for future hurricanes were all associated with a much higher standard deviation and a maximum value, indicating that the household's decision was altered having experienced a long period of electricity disruption. These comparative results suggested that,

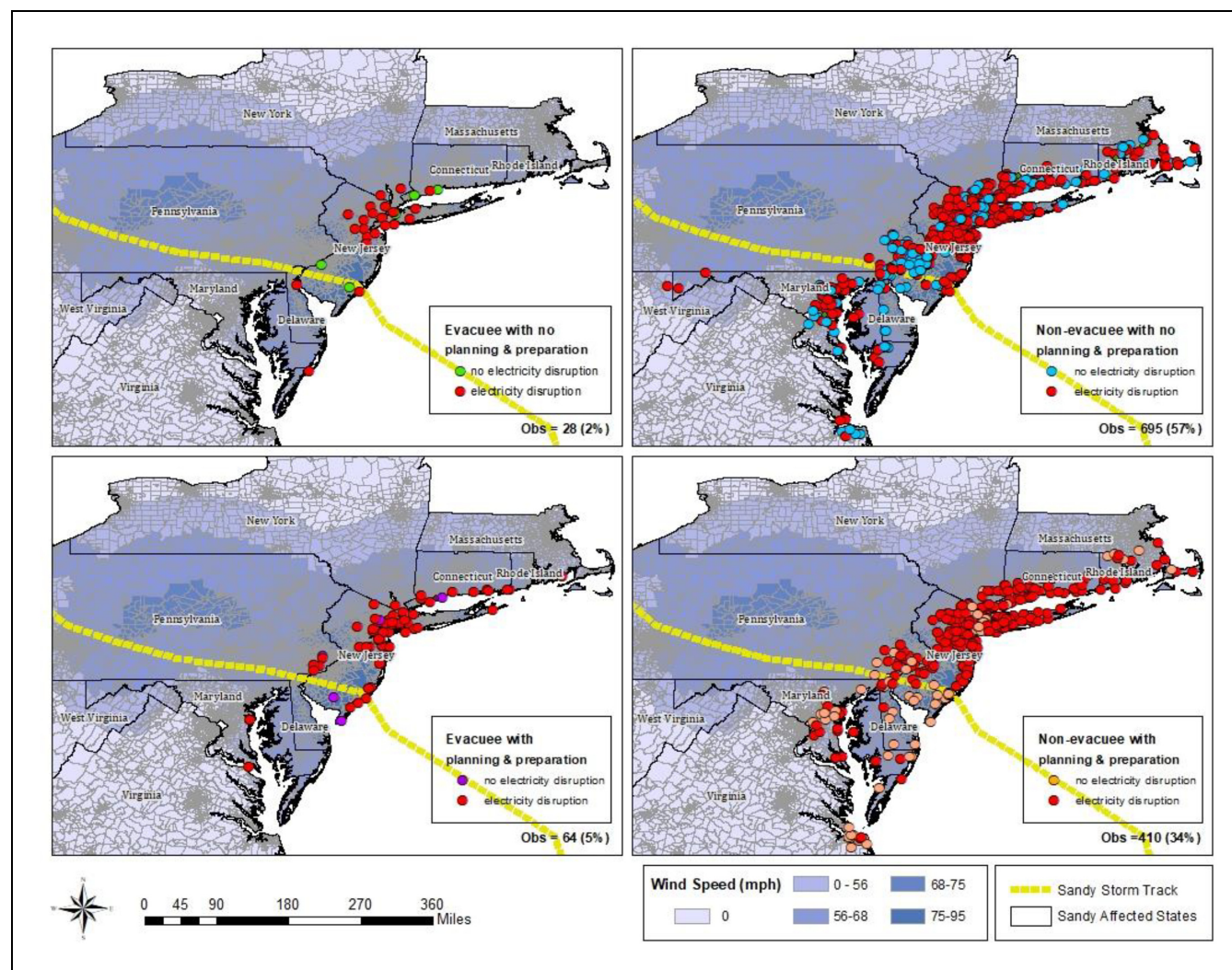


Figure 3. Spatial distribution of the effect of electricity disruption and evacuation behavior on future evacuation planning and preparedness.

Note: Evacuated during Hurricane Sandy (yes/no); experienced electricity disruption (yes/no); have you made the necessary preparations to leave your home to go someplace safer in the event of a hurricane this year? OR does your household have an evacuation plan in case a hurricane hits your neighborhood this year? (yes/no).

although past evacuation experience mattered, having suffered electricity disruptions created an additional incentive to initiate preparedness activities for future evacuation among these households.

We repeated this analysis to examine the effect of water disruptions on households' future preparedness and planning behavior. However, our results were slightly mixed, possibly because of the significantly lower percentage of households experiencing water disruptions (see Figure 4). As shown in Table 4, we did not find water disruptions to be an influential factor in households' preparedness or planning decisions among evacuees. Of those who confirmed future evacuation preparedness, 31.75% had experienced water disruptions, whereas 33.33% of those who answered no to future preparedness

had experienced such disruptions. However, water disruption was shown to be influential among non-evacuees: 13.4% of those who planned or had prepared to evacuate reported water disruption, whereas only 12.13% of those who said no reported water disruption. Nonetheless, the differences were very small for both evacuee and non-evacuee groups, we therefore undertook regression analysis to identify whether there were any statistically significant impacts of water disruptions.

For the robustness check, we employed the spatial probit model to examine whether there were any spatial dependencies among household decisions. However, the spatial dependence parameter, ρ , was not statistically significant for any of the models; the spatial model, therefore, did not provide additional information. The models

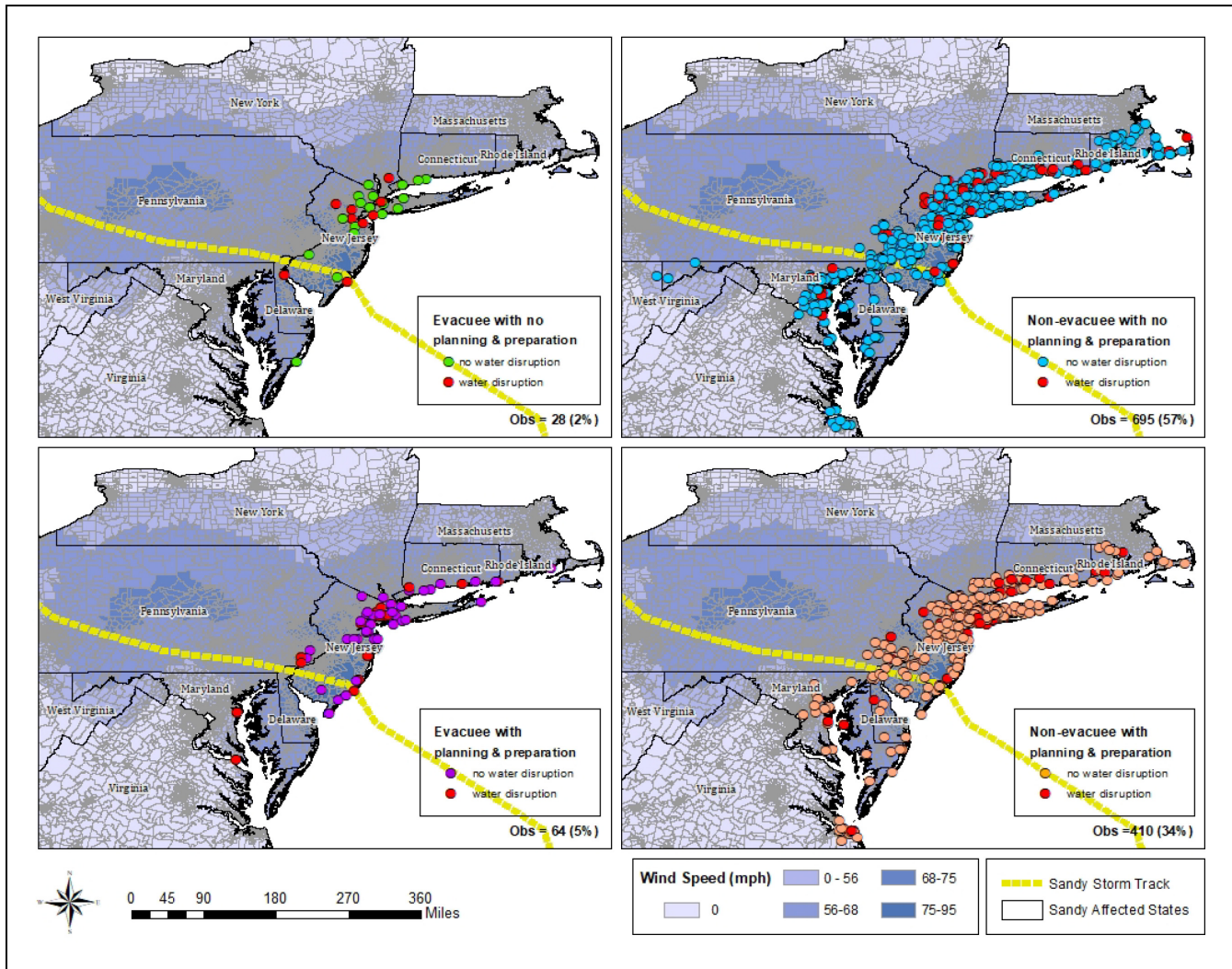


Figure 4. Spatial distribution of the effect of water disruption and evacuation behavior on future evacuation planning and preparedness. Note: Evacuated during Hurricane Sandy (yes/no); experienced water service disruption (yes/no); have you made the necessary preparations to leave your home to go someplace safer in the event of a hurricane this year? OR does your household have an evacuation plan in case a hurricane hits your neighborhood this year? (yes/no).

Table 4. Effects of Electricity Disruptions and Past Evacuation Behavior on Hurricane Planning and Preparedness

Number of respondents	Experienced disruption (count)	Experience disruption (%)	Average days of disruption	SD	Min.	Max.
Group 1—Evacuee with no evacuation planning/preparedness ($n = 28$)						
28	22	78.57	7.39	11.44	0	60
Group 2—Evacuee with evacuation planning/preparedness ($n = 64$)						
63	58	92.06	10.35	24.89	0	200
Difference between evacuees (Group 1 and Group 2)	+35	+13.49	+2.96	+	0	+140
Group 3—Non-evacuee with no evacuation planning/preparedness ($n = 695$)						
683	462	67.64	3.86	4.84	0	70
Group 4—Non-evacuee with evacuation planning/preparedness ($n = 410$)						
407	314	77.15	4.85	12.97	0	250
Difference between non-evacuees (Group 3 and Group 4)	-276	+9.51	0.99	+	0	+180

Note: SD = standard deviation; Min. = minimum; Max. = maximum.

Table 5. Effects of Water Disruptions and Past Evacuation Behavior on Hurricane Planning and Preparedness

Number of respondents	Experienced disruption (count)	Experience disruption (%)	Average days of disruption	SD	Min.	Max.
Group 1—Evacuee with no evacuation planning/preparedness (<i>n</i> = 28)						
27	9	33.33	4.07	12.15	0	60
Group 2—Evacuee with evacuation planning/preparedness (<i>n</i> = 64)						
63	20	31.75	5.32	25.40	0	200
Difference between Evacuees (Group 1 and Group 2)						
+36	+11	−1.58	+1.25	+	0	+140
Group 3—Non-evacuee with no evacuation planning/preparedness (<i>n</i> = 695)						
676	82	12.13	0.64	2.18	0	15
Group 4—Non-evacuee with evacuation planning/preparedness (<i>n</i> = 410)						
403	54	13.40	2.11	21.53	0	352
Difference between non-evacuees (Group 3 and Group 4)						
−243	−28	+1.27	1.47	+	0	+337

Note: SD = standard deviation; Min. = minimum; Max. = maximum.

in the spatial probit estimations showed that, although spatial dependence was not evident, experiencing electricity disruptions was found to increase the probability of preparing or planning for future hurricanes (see Table A2 in the Appendix).

Discussion and Conclusions

In recent years, hurricanes have increasingly been making landfall in the United States. Climate change has increased Atlantic hurricane activities, producing storms that are stronger and wetter (40). Within 3 years (i.e., from October 2016 to September 2019), five Category 5 Atlantic hurricanes (Dorian, Irma, Maria, Matthew, and Michael) made landfall in the United States and Puerto Rico, and two Category 4 storms (Florence and Harvey) produced torrential rain and extreme flooding (40). Continuing this trend, the 2020 season generated a record number of hurricanes (30 named hurricanes, surpassed the second-highest number on record of 28 hurricanes in 2005). Hurricane preparedness is therefore key to avoiding the extent possible of human and economic costs among affected individuals (35).

Against this backdrop, we conducted a model-building exercise coupled with a spatial analysis to assess the role of utility disruptions on future evacuation planning among residents living in hurricane-affected communities across nine U.S. states. We found that experience of power disruptions was a significant predictor of future evacuation planning, specifically, having experienced disruptions in the delivery of electricity services to their homes, residents were more likely to have an evacuation plan for a future hurricane event. With improvements in hurricane forecasting and data-driven predictions, anticipated power outage zones could be mapped and communicated ahead of time (41, 42). Such

targeted information and risk communication could be useful for promoting disaster planning both at household and community levels and could contribute to more effective disaster management.

Currently, emergency agencies' risk communication strategies typically focus on providing information on predicted hurricane paths, storm surges, and flood-risk areas. We argue that information on utility disruptions, including on the types, duration, and impacts, could also be utilized in risk communications to encourage the decision to evacuate. Information on utility disruptions has the potential to incentivize households to plan and make the necessary preparations for an evacuation, thereby reducing human suffering.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: N. Halim, F. Jiang, M. Khan, S. Meng, P. Mozumder; data collection: N. Halim, F. Jiang, M. Khan, S. Meng, P. Mozumder; analysis and interpretation of results: N. Halim, F. Jiang, M. Khan, S. Meng, P. Mozumder; draft manuscript preparation: N. Halim, F. Jiang, M. Khan, S. Meng, P. Mozumder. All authors reviewed the results and approved the final version of the manuscript.

Declaration of Conflicting Interests

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Data Accessibility Statement

Data will be made available on reasonable request subject to compliance with Institutional Review Board guidelines.

Supplemental Material

Supplemental material for this article is available online.

References

1. NOAA 2020. Fast Facts Hurricane Costs. <https://coast.noaa.gov/states/fast-facts/hurricane-costs.html>.
2. Sobanjo, J. O., P. D. Thompson, and R. Kerr. Modeling Hurricane Hazards and Damage on Florida Bridges. *Transportation Research Record: Journal of the Transportation Research Board*, 2013. 2360: 60–68.
3. Gong, J., and A. Maher. Use of Mobile Lidar Data to Assess Hurricane Damage and Visualize Community Vulnerability. *Transportation Research Record: Journal of the Transportation Research Board*, 2014. 2459: 119–126.
4. Snaiki, R., T. Wu, A. S. Whittaker, and J. F. Atkinson. Hurricane Wind and Storm Surge Effects on Coastal Bridges Under a Changing Climate. *Transportation Research Record: Journal of the Transportation Research Board*, 2020. 9: 0361198120917671.
5. STATISTA 2020. Most Expensive Natural Disasters in the United States as of April 2020. <https://www.statista.com/statistics/744015/most-expensive-natural-disasters-usa/>.
6. Wilmot, C. G., and N. Meduri. Methodology to Establish Hurricane Evacuation Zones. *Transportation Research Record: Journal of the Transportation Research Board*, 2005. 1922: 129–137.
7. Ballard, A. J. Traffic Operations for Hurricane Evacuation. *Transportation Research Record: Journal of the Transportation Research Board*, 2007. 2035: 195–204.
8. Mozumder, P., and W. F. Vásquez. An Empirical Analysis of Hurricane Evacuation Expenditures. *Natural Hazards*, Vol. 79, No. 1, 2015, pp. 81–92.
9. Mozumder, P., and W. F. Vásquez. Understanding Hurricane Evacuation Decisions Under Contingent Scenarios: A Stated Preference Approach. *Environmental and Resource Economics*, Vol. 71, No. 2, 2018, pp. 407–425.
10. Fu, H., C. G. Wilmot, H. Zhang, and E. J. Baker. Modeling the Hurricane Evacuation Response Curve. *Transportation Research Record: Journal of the Transportation Research Board*, 2007. 2022: 94–102.
11. Mongold, E., R. A. Davidson, J. Trivedi, S. DeYoung, T. Wachtendorf, and P. Anyidoho. Hurricane Evacuation Beliefs and Behavior of Inland vs. Coastal Populations. *Environmental Hazards*, October 8, 2020, pp. 1–19.
12. Halim, N., C. J. Kuhlman, A. Marathe, P. Mozumder, and A. Vullikanti. Two-Mode Threshold Graph Dynamical Systems for Modeling Evacuation Decision-Making During Disaster Events. *Proc., International Conference on Complex Networks and Their Applications*, Springer, Cham, December 10, 2019, pp. 519–531.
13. Balakrishnan, S., and Z. Zhang. Developing Priority Index for Managing Utility Disruptions in Urban Areas with Focus on Cascading and Interdependent Effects. *Transportation Research Record: Journal of the Transportation Research Board*, 2018. 2672: 101–112.
14. Barrett, B., B. Ran, and R. Pillai. Developing a Dynamic Traffic Management Modeling Framework for Hurricane Evacuation. *Transportation Research Record: Journal of the Transportation Research Board*, 2000. 1733: 115–121.
15. Hu, H., H. Ma, J. He, B. Li, and Y. Gao. Coupling Influence of Multiple Disruptions in Supply Chain. *International Journal of Industrial and Systems Engineering*, Vol. 35, No. 2, 2020, pp. 135–157.
16. Yates, A. A Framework for Studying Mortality Arising from Critical Infrastructure Loss. *International Journal of Critical Infrastructure Protection*, Vol. 7, No. 2, 2014, pp. 100–111.
17. Craun, G. F., and R. L. Calderon. Waterborne Disease Outbreaks Caused by Distribution System Deficiencies. *Journal-American Water Works Association*, Vol. 93, No. 9, 2001, pp. 64–75.
18. Kile, J. C., S. Skowronski, M. D. Miller, S. G. Reissman, V. Balaban, R. W. Klomp, D. B. Reissman, H. M. Mainzer, and A. L. Dannenberg. Impact of 2003 Power Outages on Public Health and Emergency Response. *Prehospital and Disaster Medicine*, Vol. 20, No. 2, 2005, pp. 93–97.
19. Turner, D. S., W. A. Evans, M. Kumalachew, B. Wolshon, V. Dixit, V. P. Sisiopiku, S. Islam, and M. D. Anderson. Issues, Practices, and Needs for Communicating Evacuation Information to Vulnerable Populations. *Transportation Research Record: Journal of the Transportation Research Board*, 2010. 2196: 159–167.
20. Zhang, C., W. Yao, Y. Yang, R. Huang, and A. Mostafavi. Semiautomated Social Media Analytics for Sensing Societal Impacts Due to Community Disruptions During Disasters. *Computer-Aided Civil and Infrastructure Engineering*, Vol. 35, No. 12, 2020, pp. 1331–1348.
21. Severson, J. C., V. Maier-Sperdelozzi, J. H. Wang, and C. E. Collyer. Rhode Island Transportation System in Natural or Human-Caused Disasters: Enhancing Preparedness and Response. *Transportation Research Record: Journal of the Transportation Research Board*, 2008. 2041: 68–79.
22. Gao, Y., Y. C. Chiu, S. Wang, and S. Küçükyavuz. Optimal Refueling Station Location and Supply Planning for Hurricane Evacuation. *Transportation Research Record: Journal of the Transportation Research Board*, 2010. 2196: 56–64.
23. Cheng, G., C. G. Wilmot, and E. J. Baker. Dynamic Gravity Model for Hurricane Evacuation Planning.

- Transportation Research Record: Journal of the Transportation Research Board*, 2011. 2234: 125–134.
24. Gudishala, R., and C. Wilmot. Modeling Emergency Managers' Hurricane Evacuation Decisions. *Transportation Research Record: Journal of the Transportation Research Board*, 2017. 2604: 82–87.
 25. West, C. T., and D. G. Lenze. Modeling the Regional Impact of Natural Disaster and Recovery: A General Framework and an Application to Hurricane Andrew. *International Regional Science Review*, Vol. 17, No. 2, 1994, pp. 121–150.
 26. Whitehead, J. C., B. Edwards, M. Van Willigen, J. R. Maiolo, K. Wilson, and K. T. Smith. Heading for Higher Ground: Factors Affecting Real and Hypothetical Hurricane Evacuation Behavior. *Global Environmental Change Part B: Environmental Hazards*, Vol. 2, No. 4, 2000, pp. 133–142.
 27. Dash, N., and H. Gladwin. Evacuation Decision Making and Behavioral Responses: Individual and Household. *Natural Hazards Review*, Vol. 8, No. 3, 2007, pp. 69–77.
 28. Lazo, J. K., A. Bostrom, R. E. Morss, J. L. Demuth, and H. Lazrus. Factors Affecting Hurricane Evacuation Intentions. *Risk Analysis*, Vol. 35, No. 10, 2015, pp. 1837–1857.
 29. Vásquez, W. F., T. J. Murray, and P. Mozumder. Understanding Hurricane Evacuation Planning in the Northeastern and Mid-Atlantic United States. *Natural Hazards Review*, Vol. 17, No. 1, 2016, p. 04015018.
 30. Fu, H., and C. G. Wilmot. Sequential Logit Dynamic Travel Demand Model for Hurricane Evacuation. *Transportation Research Record: Journal of the Transportation Research Board*, 2004. 1882: 19–26.
 31. Fu, H., and C. G. Wilmot. Survival Analysis-Based Dynamic Travel Demand Models for Hurricane Evacuation. *Transportation Research Record: Journal of the Transportation Research Board*, 2006. 1964: 211–218.
 32. Solís, D., M. Thomas, and D. Letson. An Empirical Evaluation of the Determinants of Household Hurricane Evacuation Choice. *Journal of Development and Agricultural Economics*, Vol. 2, No. 5, 2010, pp. 188–196.
 33. Sadri, A. M., S. V. Ukkusuri, P. Murray-Tuite, and H. Gladwin. Hurricane Evacuation Route Choice of Major Bridges in Miami Beach, Florida. *Transportation Research Record: Journal of the Transportation Research Board*, 2015. 2532: 164–173.
 34. Chatterjee, C., and P. Mozumder. Hurricane Wilma, Utility Disruption, and Household Wellbeing. *International Journal of Disaster Risk Reduction*, Vol. 14, 2015, pp. 395–402.
 35. Mayer, B. W., J. Moss, and K. Dale. Disaster and Preparedness: Lessons from Hurricane Rita. *Journal of Contingencies and Crisis Management*, Vol. 16, No. 1, 2008, pp. 14–23.
 36. Carlsson, F., P. Frykblom, and C. Liljenstolpe. Valuing Wetland Attributes: An Application of Choice Experiments. *Ecological Economics*, Vol. 47, No. 1, 2003, pp. 95–103.
 37. Huang, S. K., M. K. Lindell, C. S. Prater, H. C. Wu, and L. K. Siebeneck. Household Evacuation Decision Making in Response to Hurricane Ike. *Natural Hazards Review*, Vol. 13, No. 4, 2012, pp. 283–296.
 38. Huang, S. K., M. K. Lindell, and C. S. Prater. Multistage Model of Hurricane Evacuation Decision: Empirical Study of Hurricanes Katrina and Rita. *Natural Hazards Review*, Vol. 18, No. 3, 2017, p. 05016008.
 39. Goel, K. J., S. A. Thakur, J. L. Levy, C. R. Dhanaraj, E. Carmi, J. R. Provine, E. K. Moxley, and inventors; Google LLC, assignee. Knowledge Panel. *United States Patent US 10,019,495*, July 10, 2018.
 40. Shultz, J. M., J. P. Kossin, A. Hertelendy, F. Burkle, C. Fugate, R. Sherman, J. Bakalar, K. Berg, A. Maggioni, Z. Espinel, and D. E. Sands. Mitigating the Twin Threats of Climate-Driven Atlantic Hurricanes and COVID-19 Transmission. *Disaster Medicine and Public Health Preparedness*, Vol. 14, No. 4, 2020, pp. 494–503.
 41. Staid, A., S. D. Guikema, R. Nateghi, S. M. Quiring, and M. Z. Gao. Simulation of Tropical Cyclone Impacts to the US Power System Under Climate Change Scenarios. *Climatic Change*, Vol. 127, No. 3–4, 2014, pp. 535–546.
 42. McRoberts, D. B., S. M. Quiring, and S. D. Guikema. Improving Hurricane Power Outage Prediction Models Through the Inclusion of Local Environmental Factors. *Risk Analysis*, Vol. 38, No. 12, 2018, pp. 2722–2737.