TRR
JOURNAL OF THE TRANSPORTATION RESEARCH BOARD

Research Article

Transportation Research Record
2022, Vol. 2676(5) 358–372

DOI: 10.1177/03611981211066901
journals.sagepub.com/home/trr
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Departure Timing Preference during Extreme Weather Events: Evidence from Hurricane Evacuation Behavior

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Abstract

Hurricane evacuation has become an increasingly complicated activity in the U.S. as it involves moving many people who live along the Atlantic coast and Gulf coast within a very limited time. A good deal of research has been conducted on hurricane evacuation, but only a limited number of studies have looked into the timing aspect of evacuation. This paper intends to contribute to the literature on evacuation timing decisions by investigating what factors influence the time preference at the household level. Two hurricane survey data sets were used to analyze household evacuation behaviors across the Gulf coast as well as the Northeast and Mid-Atlantic coast in a comparative perspective. Using the Heckman selection model, we examined various factors identified in the literature on the two possible outcomes (evacuation and early evacuation). We found that the most important determinants of evacuation were prior evacuation experience, evacuation orders, and risk perceptions, while the most important determinants of early evacuation were prior evacuation experiences, days spent at the evacuation destination, and the cost of evacuation. Socioeconomic factors also influenced the two decisions but differently. These results provide implications for future hurricane evacuation planning and for improving emergency management practices.

Keywords

sustainability and resilience, transportation systems resilience, disaster response, recovery, and business continuity, emergency evacuation, natural hazards and extreme weather events

In the past few decades, hurricanes have become one of the deadliest natural disasters affecting coastal areas of the U.S. (*1, 2*). We saw a total of seven Category 5 hurricanes during the 2016–2020 Atlantic hurricane seasons (2016: Matthew, 2017: Irma and Maria, 2018: Michael, 2019: Dorian and Lorenzo, 2020: Iota). While fighting the COVID-19 pandemic in 2020, U.S. coastal residents had to respond to a historically active hurricane season spawning 30 tropical storms, including 12 U.S. landfalls (*3*). Although hurricane evacuation has been demonstrated to be an effective option to reduce hurricane-related deaths, it is becoming an increasingly complicated activity since many people need to evacuate quickly and efficiently within a limited time (*4, 5*). Mass hurricane evacuations lead to high traffic congestion and possible damage to road networks (*6–8*). It is essential for social scientists and community planners to better understand people's hurricane evacuation behavior to devise an effective evacuation plan for coastal residents (*9, 10*).

Perry et al. stated three critically important factors affecting evacuation decision-making: (1) the receipt of warning and information, (2) the level of perceived risks, and (3) the existence of a preparedness plan (*11*). Since then, researchers have empirically examined these factors. Evacuation advisories or orders were found to be a strong driver in motivating households to take action and evacuate (*12–14*). Weller et al. (*15*) presented a study to understand residents who failed to comply with the

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evacuation order and found that non-evacuees were associated with a lower degree of perceived risk. Dash and Morrow (*16*) identified perceived risks as the most critical determinant for whether to evacuate or not. Gladwin et al. (*17*) showed how household evacuation decisions were restrained by the level of perceptions and the time available to prepare for the hurricane. Karaye et al. (*18*) found that higher perceptions of both storm surge risk and wind risk were significant predictors for evacuation.

While confirming the influence of evacuation warning and risk perceptions, researchers have also identified other factors that shape evacuation decisions, such as the ability of housing to withstand a hurricane, geographic location, the decisions of influential people (neighbors, family, or friends), and sociodemographic characteristics of the individual and family members (*19–22*). Irwin and Hurlbert (*23*) found that besides risk perceptions, gender, age, and housing type significantly influenced evacuation decisions during Hurricane Andrew. Bateman and Edwards (*24*) indicated that women were more likely to evacuate because of their higher risk perceptions compared with men. Whitehead et al. (*25*) indicated that the strongest predictor of evacuation was storm intensity, followed by evacuation orders, perceived flood risk, and living in mobile homes. Peacock et al. (*26*) found that having flood insurance and strong home structures were negatively associated with evacuation because households perceived lower risk of storm damage. Stein et al. (*27*) pointed out that evacuation decisions also depend on the geographic location, as risk perceptions are not uniform across the hurricane-threatened areas. Mozumder and Vásquez (*28*) indicated that providing financial assistance (e.g., vouchers) to cover evacuation expenses can increase the probability of evacuation.

Previous studies have reported that past evacuation experience played an important role in people's future evacuation decisions and preparation (*29*). Riad et al. (*30*) concluded that prior evacuation experience was the best predictor of household evacuation during Hurricanes Hugo and Andrew. However, inconsistent results were also identified in the literature. Baker (*12*) found previous hurricane experience had only minor effects on evacuation and discussed the problem of "false experience." Riad (*31*) claimed that past evacuation experience was strongly associated with future evacuation behavior. Dash and Morrow (*16*) stated that people who experienced traffic delays returning after a hurricane evacuation were less likely to evacuate for the next hurricane, but risk perception can dominate the negative hurricane evacuation experience. Meyer et al. (*32*) found that households without past hurricane experiences were actually the most likely to express worry about the storm and fastest to undertake preventive actions. Huang et al. (*33*) indicated that hurricane experiences positively affected evacuation decisions, but unnecessary evacuation experience can become an impedient.

Despite numerous studies that contributed to understanding household evacuation behaviors, only a few studies investigated evacuation timing decisions and factors that influence such decisions. Earlier research has focused on the traffic problems and logistic issues during the hurricane evacuation. Dow and Cutter (*34*) concluded that understanding how people evacuate is an important and emerging issue for evacuation traffic planning, based on the evidence that 25% of households took more than one car and almost half of the evacuees left within the same 6-h period. Lindell et al. (*35*) argued that traffic congestion could cause 10–20 h of delays if the evacuation process is not managed correctly. Furthermore, if an evacuation route runs parallel to bays and rivers, storm surge and flooding could cause massive loss of lives among the evacuees stuck in the traffic congestion (*36*). As such, further research is needed to better understand the time preferences at the household level and incorporate the dynamics of human behavior into evacuation modeling (*19, 37*).

Sorensen (*38*) presented one of the earliest studies to examine individual variation in the evacuation timing behavior during an emergency fire event. Fu and Wilmot (*39*) developed a sequential logit model to predict the probability that an individual will evacuate in each period before hurricane landfall. Hasan et al. (*40*) proposed a probabilistic model to study evacuation timing decisions, whereas traditional quantitative methods relied on response curves to predict the evacuation rate in each departure time interval. Moreover, instead of using a hypothetical hurricane scenario, they studied the timing of evacuation for households who were affected by a hurricane. Their results showed that evacuation notice, location, destination choice, and socioeconomic status were key determinants of early evacuation. Sarwar et al. (*41*) developed a random-parameters logit model and identified that coastal flooding, voluntary and mandatory orders, mobile home, and sociodemographic factors played essential roles in evacuation time decisions. Gehlot et al. (*42*) constructed a model to jointly estimate evacuation departure time and travel time. They found households who lived closer to the hurricane path were more concerned, and that those who believed that they had been ordered to leave evacuated earlier. The elderly, those who relied on local television stations, and those who lived alone were likely to depart later. Pham et al. (*43*) found that variations in evacuation departure time were determined by experience, receipt of an evacuation order, and discussions about the evacuation order with others.

The present study contributes to the literature by understanding households' evacuation timing decisions and the factors influencing earlier versus later evacuation among evacuees. We use two data sets from households who experienced Hurricane Ike (collected by a telephone survey) and Hurricane Sandy (collected from an online survey). Most of the previous literature measured time and risk preferences separately; however, time and risk preferences need to be measured together to account for potential cross-correlation. A few researchers have attempted to measure the two preferences together in the presence of a natural disaster, but not in the context of a hurricane evacuation. Cassar et al. (*44*), using experimental evidence from the 2004 tsunami, found that natural disasters can change an individual's risk and time preference. Callen (*45*) illustrated that tsunami exposure affected an individual's time preference and estimated increased patience among Sri Lankan workers. In this study, we simultaneously estimate the rate of time preference and the coefficient of risk aversion using reference-dependent utility models. Based on the Heckman selection approach, we analyze the relationship between hurricane time and risk preferences under the reference point of past evacuation experience. We also examine the role of other relevant factors studied in the literature, including evacuation orders, risk perceptions, insurance, mobile home, and other household sociodemographic characteristics.

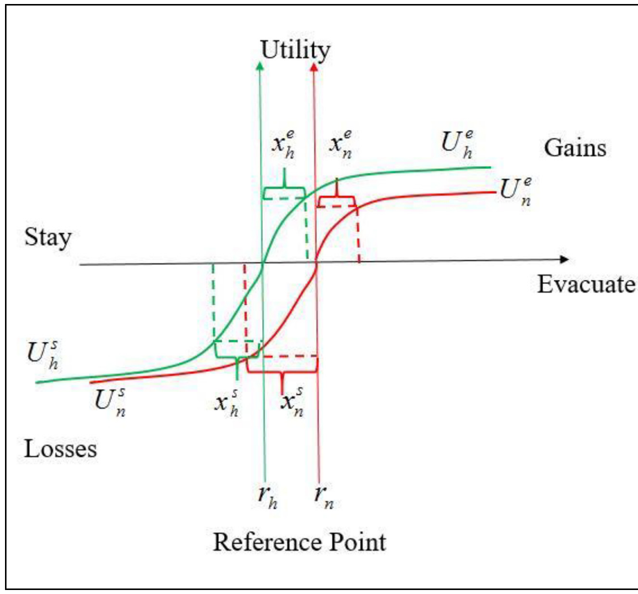

Figure 1. Utility comparison and reference point with hurricane evacuation experience.

Analytical Framework and Empirical Modeling

This section describes a theoretical framework of people's evacuation decision (risk preference) and departure time (time preference) associated with an individual's experience of avoiding hurricane risks. The theoretical framework is based on a model of reference-dependent preferences, which depend on utility comparisons to relevant reference levels (*46*). The reference-dependent utility theory explains people's decisions based on the potential value of losses rather than the outcome (*47*). Kőszegi and Rabin (*48*) extended the models of reference-dependent preferences and loss aversion. Loss aversion is one of the key properties of reference-dependent preferences, one which indicates that people dislike losses against the reference point more than they like gains of the same amount. Most of the literature on reference-dependent preferences has previously been published in the domain of behavioral economics. For example, Liu and Han (*49*) investigated reference dependence on user search interaction and satisfaction from a behavioral economics perspective and defined a reference point to predict users' search decisions.

However, the empirical analysis of reference-dependent models has not taken place in the context of an extreme weather event, particularly for hurricane evacuation decision-making. In this study, we assume that people have a reference point when making hurricane evacuation decisions, which can be based on prior hurricane evacuation experience. People who choose not to evacuate and stay at home during a hurricane event can expect to live their normal lives, provided that they are not affected by the hurricane. Evacuating (compared with staying home) entails a sense of loss of normal lifestyle because evacuees need to give up the comfort of living in their own home and spend money on transportation, food, and lodging, as well as experiencing other inconveniences when they are away from home. Conversely, people who choose to stay can suffer major discomfort (because of utility disruptions to electricity, water, phone, transportation, and so forth; see Meng and Mozumder [*50*]), damage to their homes, and even risk to their lives if they are hit by a hurricane. In that case, evacuees will enjoy the benefit of avoiding the risk to their lives and the associated discomfort.

In accordance with Kőszegi and Rabin's (*48*) models of reference-dependent preferences, we formulate the reference-dependent utility of an individual based on two reference-dependent points (Figure 1):

$$V_h = \lambda U_h^e(x_h^e - r_h) + (1 - \lambda)U_h^s(x_h^s - r_h) \quad (1)$$

$$V_n = \lambda U_n^e(x_n^e - r_n) + (1 - \lambda)U_n^s(x_n^s - r_n) \quad (2)$$

where

V_h is the total utility of an individual who has had prior hurricane evacuation experience and V_n is the total utility of an individual with no hurricane evacuation experience;

U_h^e is the utility of evacuees who have hurricane evacuation experience, U_n^e is the utility of evacuees who have no hurricane evacuation experience, and λ is the probability of hurricane evacuation;

U_h^s is the utility of an individual with prior hurricane evacuation experience, but who choose to stay home, and U_n^s is the utility of an individual without experience and who chooses to stay home;

x^e presents the time when evacuees decide to leave, and x^s is the time when non-evacuees make the decision to stay home;

r_h is the reference point of the individual who has hurricane evacuation experience, and r_n is the reference point of the individual with no experience.

We assume that the utility of the evacuees with hurricane evacuation experience is greater than the utility of the evacuees without experience, which is $U_h^e > U_n^e$ (because of the preference for loss aversion; see Abdellaoui et al. [*51*]).

For the empirical analysis, we use the Heckman selection model (*52*) because we first need to identify people who choose to evacuate, and then look into the timing of their evacuation. Heckman (*53*) provided a two-stage estimation procedure using the inverse Mills ratio to address the possible selection bias. Cameron and Trivedi (*54*) and Greene (*55*) extended the Heckman model to better accommodate the various forms of the dependent variables. In the first step, a probit model is estimated to observe a positive outcome of the dependent variable (Equation 3). The estimated parameters are used to calculate the inverse Mills ratio, which is then included as an extra explanatory variable in the second-stage regression estimation (Equation 4).

$$Y_1 = \alpha Z + u \text{ Selection equation} \tag{3}$$

$$Y_2 = \beta X + \rho\sigma_u M(\alpha Z) + \varepsilon \text{ Regression equation} \tag{4}$$

where

Y_1 is the dichotomous dependent variable representing the risk preference (i.e., whether to evacuate or not) and Y_2 is the dependent variable of interest representing time preference (i.e., time to evacuate), with the value of Y_2 being observed only when Y_1 is observed to have a specific outcome (evacuation in this case), because we cannot observe the timing information among non-evacuees;

X and Z represent matrices of covariates including the relevant determinants of evacuation decision and time preferences studied in the literature;

α and β are the vectors of coefficients to be estimated;

ρ is the correlation between unobserved determinants of evacuation decision u and unobserved determinants of evacuation time preferences ε;

σ_u is the standard deviation of u; and

M is the inverse Mills ratio evaluated at αZ.

To account for the potential cross-correlation in Equations 3 and 4, risk preferences Y_1 and time preferences Y_2 are jointly estimated.

Accordingly, we test the following hypotheses:

$H_1 : \rho > 0$;
$H_2 : \alpha_{\text{EXPERIENCE}} > 0$ and/or $\beta_{\text{EXPERIENCE}} > 0$;
$H_3 : \beta_{\text{HOUSEHOLD}} > 0$

The first hypothesis (H_1) is to test the selection bias to see if the unobserved determinants of risk preferences and the unobserved determinants of evacuation time preferences are correlated. The second hypothesis (H_2) is based on the reference point assuming that individuals who had hurricane evacuation experience are more likely to evacuate. Among evacuees, those with experience also choose to evacuate earlier than those without experience. According to the third hypothesis (H_3), household characteristics are also important predictors for explaining the variation in evacuation risk and time preferences.

Survey Data and Sample Characteristics

On September 13, 2008, Hurricane Ike made landfall on Galveston Island, Texas, with sustained winds of 110 mph, a 22-ft storm surge, and widespread coastal flooding. Hurricane Ike affected mostly Texas, Louisiana, and Arkansas, causing at least 84 deaths and approximately US$19.3 billion insured losses. The total damage caused by Ike was estimated at US$24.9 billion, making it the sixth costliest Atlantic hurricane (*56*). To understand the factors that influence the evacuation timing decisions, researchers at the Florida International University conducted a telephone survey consisted of 1,099 households located in Harris and Galveston Counties in Texas. The survey was based on a random probability sample and a geocoded zip code area stratified sampling frame was employed to oversample areas of higher risks of storm surge (delineated by Federal Emergency Management Agency [FEMA]). During the phone interview, residents were asked to report the behaviors they adopted to lower their risk during Hurricane Ike's impact on the coast of Texas. Respondents who evacuated because of Ike were asked how many days before the landfall they evacuated. Information on their previous evacuation experience, receipt of mandatory or voluntary orders, concerns, risk perceptions, and socioeconomic characteristics were also collected.

Later on, in the 2012 Atlantic hurricane season, many residents from the Mid-Atlantic coastal areas experienced the highly destructive Hurricane Sandy, which at the time was marked as the second costliest natural disaster ever to affect the United States, surpassed by only Hurricane Katrina (*57*). Hurricane Sandy affected 24 states,

Table 1. Definitions and Descriptive Statistics of Variables Used for Hurricane Ike

Variable Name	Description	Mean	SD
EVAC	If the respondent evacuated for Hurricane Ike (1 = yes, 0 = otherwise)	0.48	0.50
TIME	The departure time of the evacuees for Hurricane Ike (0 = the day Ike hit .... 6 = 6 days before Ike hit)	1.82	0.98
EXPERIENCE	If the respondent evacuated for Hurricane Rita before (1 = yes, 0 = otherwise)	0.59	0.49
VOLUNTARY	If the respondent received a voluntary order to evacuate (1 = yes, 0 = otherwise)	0.26	0.44
MANDATORY	If the respondent received a mandatory order to evacuate (1 = yes, 0 = otherwise)	0.30	0.46
IMORDER	If the respondent thought the evacuation orders given by the government are important (1 = yes, 0 = otherwise)	0.36	0.48
IMPETS	If the respondent thought the needs of pets or animals are important (1 = yes, 0 = otherwise)	0.36	0.48
IMPSURGE	If the respondents considered the possibility of flooding to be important (1 = yes, 0 = otherwise)	0.37	0.48
IMPCRIME	If the respondent thought protecting home from crime and looting is important (1 = yes, 0 = otherwise)	0.42	0.49
NEIGHBOR	If the respondent's neighbors influenced their evacuation decisions (1 = yes, 0 = otherwise)	0.13	0.33
DAYS	The number of days the respondent was away from home when evacuated	9.22	18.42
INDEXP	Mean evacuation expenditures of individual (US$)	324.72	770.13
LAIDOFF	If the respondent was laid off from work because of Hurricane Ike (1 = yes, 0 = otherwise)	0.10	0.30
INCOME	Households' annual income in intervals of US$10,000 (1 = US$10,000 or less .... 11 = over US$100,000)	6.33	3.52
HHSIZE	The number of individuals living in the respondent's household	2.66	1.56
EDUC	If the respondent had a college degree (1 = yes, 0 = otherwise)	0.52	0.50
AGE	The respondent's age (in years)	58.84	15.67
GENDER	Gender of the respondent (1 = male, 0 = female)	0.33	0.47
RACE	If the respondents identified themselves as white (1 = yes, 0 = otherwise)	0.77	0.37
CHILDREN	If the respondent had children(1 = yes, 0 = otherwise)	0.17	0.37
OWNER	If the respondent owned the house (1 = yes, 0 = otherwise)	0.88	0.33
MOBILE	If the respondent's home was a mobile home (1 = yes, 0 = otherwise)	0.10	0.29
WINDOW	If the respondent installed window protection against hurricanes (1 = yes, 0 = otherwise)	0.51	0.50

Note: SD = standard deviation.

including the entirety of Eastern coastal states from Florida to Maine and the Midwestern regions to Michigan and Wisconsin. New York and New Jersey were the most severely affected states near the landfall location. At least 287 people in seven counties lost their lives, and the total property damage was approximately US$65 billion (estimates as of June 2013) in the United States (*58*). In 2013, researchers at Florida International University conducted an online survey consisted of 1,212 households who lived in Hurricane Sandy's influence areas. The households were randomly selected through a probability-based sampling from the KnowledgePanel by GfK, a probability-based web panel. A post-stratification adjustment was also employed based on demographic distributions from the Current Population Survey (CPS), to reduce the effects of any non-response and non-coverage bias. Respondents were asked similar questions on whether they evacuated during Sandy, and if so, about how many days in advance they evacuated.

Tables 1 and 2 summarize the definitions and descriptive statistics of variables used in the study analyzing evacuation behavior. During Hurricane Ike, 48% of the respondents chose to evacuate. To examine the role of past hurricane experience, respondents were asked if they had previously evacuated for Hurricane Rita, a similar hurricane that struck the Gulf of Mexico in 2005. Approximately 59% reported having evacuation experience from Rita. Among those, 35% evacuated for Hurricane Ike and 24% did not (see Figure 2). During Hurricane Sandy, only 8% of the respondents chose to evacuate and 4% reported that they had past evacuation experience from Hurricane Irene (see Figure 2). Hurricane Irene was a major hurricane that hit the East Coast of the U.S. in 2011.

Figure 3 presents the distribution of evacuation timing decisions among the evacuees during Hurricanes Ike and Sandy. Most of the evacuees chose to evacuate 2 days before the landfall of Hurricane Ike (mean is 1.82 days with a standard deviation of 0.98 days). Conversely, 90% of Hurricane Sandy evacuees departed home 1 day before or on the same day when Sandy made landfall (mean is 1.07 days with a standard deviation of 3.54 days). Among Ike evacuees, the mean departure time was 1.87 days

Table 2. Definitions and Descriptive Statistics of Variables Used for Hurricane Sandy

Variable Name	Description	Mean	SD
EVAC	If the respondent evacuated for Hurricane Sandy (1 = yes, 0 = otherwise)	0.08	0.26
TIME	The departure time of the evacuees for Hurricane Sandy (0 = the day Sandy hit .... 6 = 6 days before Sandy hit)	1.07	3.54
EXPERIENCE	If the respondent evacuated for Hurricane Irene before (1 = yes, 0 = otherwise)	0.04	0.20
ORDER	If the respondent's household told by a government or news broadcast to evacuate their home (1 = yes, 0 = otherwise)	0.08	0.27
PLAN	If the respondent's household had a hurricane evacuation plan (1 = yes, 0 = otherwise)	0.34	0.47
PREPARE	If the respondent's household made the necessary preparations (1 = yes, 0 = otherwise)	0.28	0.45
INSURANCE	If the respondent had an insurance policy to cover damages to their home from a storm or hurricane (1 = yes, 0 = otherwise)	0.59	0.49
FLOOD	If the respondent's household lived in a flood zone (1 = yes, 0 = otherwise)	0.13	0.34
DAYS	The number of days the respondent was away from home when evacuated	1.64	2.41
INDEXP	Mean evacuation expenditures of individual (US$)	199.92	442.77
HHSIZE	The number of individuals living in the respondent's household	2.49	1.28
AGE	The respondent's age (in years)	52.91	15.43
GENDER	Gender of the respondent (1 = male, 0 = female)	0.40	0.49
RACE	If the respondents identified themselves as the white (1 = yes, 0 = otherwise)	0.80	0.40
SENIOR	The number of seniors in the respondent's household	2.47	0.77
HEAD	If the respondent was the head of their household (1 = yes, 0 = otherwise)	0.87	0.34
DISABLES	The number of disabled in the respondent's household	2.17	0.54
SMOKE	If the respondent smoked (1 = yes, 0 = otherwise)	0.10	0.29
YEARS	The number of years lived in the house	23.85	19.17
OWNER	If the respondent owned the house (1 = yes, 0 = otherwise)	0.78	0.41
VEHICLES	The number of vehicles in the respondent's household	3.87	1.18
WINDOW	If the respondent installed window protection against hurricanes (1 = yes, 0 = otherwise)	0.05	0.23

Note: SD = standard deviation.

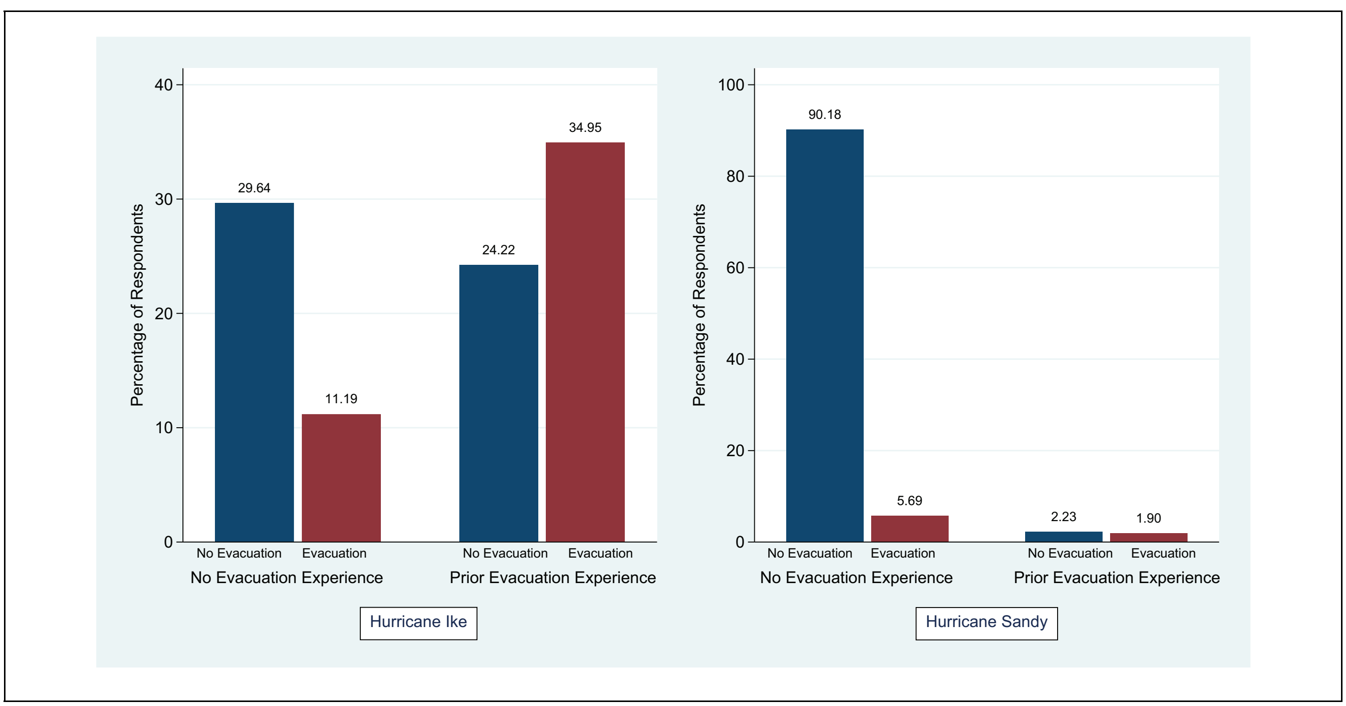

Figure 2. Evacuation decision among respondents with and without prior evacuation experience.

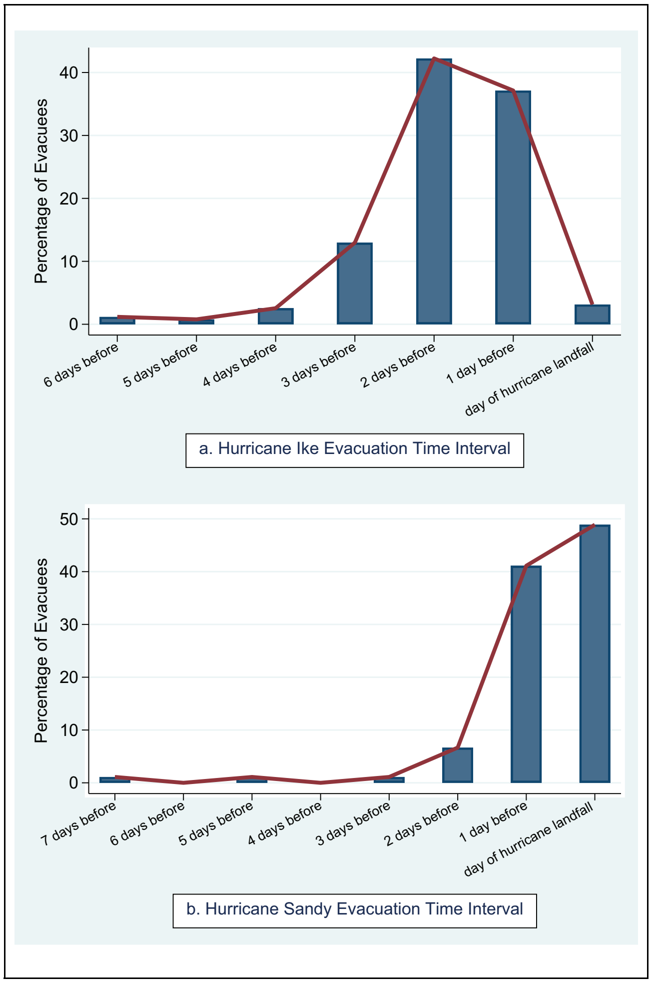

Figure 3. Hurricane evacuation time interval during (*a*) Hurricane Ike and (*b*) Hurricane Sandy.

before the landfall for those with past evacuation experience and 1.53 days before the landfall for those without evacuation experience. The difference is more significant among Sandy evacuees. The mean departure time was 2.48 days before the landfall for those with past evacuation experience, and only 0.59 days for those without experience. These descriptive statistics indicate that people who had past evacuation experience evacuated earlier than those who did not have a similar experience. In the empirical analysis, we investigate whether the respondents with hurricane evacuation experience evacuated sooner rather than later.

Apart from the variable EXPERIENCE (prior hurricane evacuation experience), we have included a list of relevant explanatory variables used in the literature. For examples, following Whitehead (*59*), the binary indicators VOLUNTARY (received a voluntary evacuation order) and MANDATORY (received a mandatory evacuation order) are included as an indicator of location-specific hurricane risk. The binary indicators IMPSURGE (if the respondents considered the possibility of flooding was important) and IMPCRIME (if the respondents considered that protecting home from crime and looting was important) are incorporated as control variables that can influence individuals' risk and time preferences during a hurricane event. The binary indicator WINDOW (if the respondent had window protection against hurricanes) is incorporated because hurricane mitigation activities adopted before the hurricane season can also influence households' evacuation decisions (*60*). Household characteristics (age, household size, education, owner, race, and gender) are also included to control for unobserved heterogeneity in risk and time preferences.

Table 1 displays the definition and descriptive statistics of all the variables used in the Hurricane Ike analysis. The average age of the respondents was 59 years old, and 33% were male. About 88% of respondents were homeowners, with an average household size of 2.7 members. Approximately 52% of respondents had a college degree. Most respondents identified themselves as white (77.1%), less than 16% were black, and 6.9% had a racial background other than white and black. More than 51% of respondents reported that they installed window protection in their housing units against hurricane risk. Approximately 26% of respondents received a voluntary order to evacuate, and 30% received a mandatory order. Approximately 10% of respondents were laid off from work because of Hurricane Ike. About 13% of respondents indicated that their neighbors affected their evacuation decisions. The mean evacuation cost was about $325 per household. In relation to the important aspects of making an evacuation decision, 37% considered the probability of flooding, 36% considered government orders, 42% considered crime and looting, and 36% thought the needs of pets and animals were important.

Table 2 shows the definition and descriptive statistics of all variables used in the Hurricane Sandy analysis. The average age of respondents was 53, and 40% were male. The average number of seniors was 2.5, and the average number of disabled was 2.17. The average years of residence were 24. Approximately 78% of respondents were homeowners, with an average household size of approximately 2.5 members. The majority of respondents (80%) identified themselves as white. More than 13% of respondents lived in the flood zone, and almost 59% reported they had an insurance policy to cover storm-induced damages. Only 8% of respondents received evacuation orders via a government agency (police or fire official) or news broadcast. Approximately 34% made an evacuation plan, 22% made the necessary evacuation preparations, but only 5% indicated that they installed

Table 3. Estimation Results of Evacuation Time Decision for Hurricane Ike

Variable Name	Model 1	Model 2	Model 3	Model 4
Panel A (Dep var: TIME [Departure time of the evacuees])				
EXPERIENCE	0.391 (0.157)**	0.471 (0.224)**	0.414 (0.216)*	0.471 (0.214)**
VOLUNTARY	NA	−0.018 (0.315)	−0.063 (0.312)	−0.016 (0.294)
MANDATORY	NA	0.453 (0.543)	0.313 (0.532)	0.465 (0.503)
IMORDER	0.393 (0.122)***	0.294 (0.178)*	0.37 (0.167)**	0.293 (0.177)*
IMPPETS	NA	−0.124 (0.183)	−0.09 (0.173)	−0.125 (0.184)
IMPSURGE	NA	0.146 (0.232)	0.045 (0.216)	0.155 (0.232)
IMPCRIME	NA	−0.086 (0.192)	−0.043 (0.188)	−0.093 (0.193)
NEIGHBOR	−0.47 (0.184)**	−0.533 (0.254)**	−0.488 (0.247)**	−0.539 (0.255)**
DAYS	0.031 (0.008)***	0.046 (0.011)***	0.047 (0.011)***	0.046 (0.011)***
INDEXP	−0.00004 (0)***	−0.001 (0)***	−0.001 (0)***	−0.001 (0)***
INCOME	NA	0.001 (0.028)	0.009 (0.027)	0.001 (0.028)
HHSIZE	NA	0.006 (0.067)	−0.01 (0.055)	0.005 (0.067)
EDUC	NA	−0.058 (0.163)	−0.048 (0.161)	−0.059 (0.163)
AGE	NA	−0.004 (0.007)	NA	−0.004 (0.007)
GENDER	NA	0.052 (0.193)	0.089 (0.188)	0.044 (0.195)
RACE	−0.277 (0.137)**	−0.583 (0.216)***	−0.568 (0.214)***	−0.582 (0.208)***
CHILDREN	NA	−0.212 (0.197)	NA	−0.204 (0.199)
OWNER	0.436 (0.187)**	0.51 (0.292)*	0.591 (0.269)**	0.531 (0.305)*
MOBILE	NA	0.195 (0.327)	NA	0.161 (0.317)
WINDOW	NA	0.064 (0.156)	NA	0.083 (0.164)
Constant	2.117 (0.245)***	1.898 (0.912)**	1.903 (0.734)**	1.882 (0.861)**
Panel B (Dep var: EVAC [Whether the respondent evacuated or not, yes = 1, no = 0])				
EXPERIENCE	0.409 (0.194)**	0.501 (0.236)**	0.498 (0.236)**	0.473 (0.242)*
VOLUNTARY	0.936 (0.202)***	0.817 (0.246)***	0.83 (0.245)***	0.816 (0.251)***
MANDATORY	2.008 (0.24)***	2.106 (0.284)***	2.098 (0.282)***	2.074 (0.288)***
IMPPETS	NA	−0.352 (0.249)	−0.348 (0.248)	−0.337 (0.255)
IMPSURGE	0.533 (0.186)***	0.799 (0.262)***	0.799 (0.262)***	0.806 (0.262)***
IMPCRIME	−0.355 (0.19)*	−0.463 (0.241)*	−0.461 (0.241)*	−0.453 (0.243)*
NEIGHBOR	NA	−0.432 (0.346)	−0.43 (0.346)	−0.485 (0.354)
INDEXP	−0.001 (0)***	−0.001 (0)*	−0.001 (0)*	−0.001 (0)*
LAIDOFF	−0.599 (0.278)**	−0.796 (0.354)**	−0.799 (0.356)**	−0.88 (0.37)**
HHSIZE	NA	−0.03 (0.09)	−0.047 (0.082)	−0.059 (0.107)
EDUC	0.028 (0.179)	−0.109 (0.219)	−0.111 (0.218)	−0.074 (0.221)
AGE	NA	0.004 (0.01)	NA	0.004 (0.01)
GENDER	−0.449 (0.187)**	−0.476 (0.224)**	−0.477 (0.224)**	−0.525 (0.231)**
RACE	−0.662 (0.239)***	−0.801 (0.304)***	−0.776 (0.298)***	−0.757 (0.308)**
CHILDREN	NA	NA	NA	0.141 (0.322)
OWNER	0.519 (0.271)*	0.586 (0.336)*	0.615 (0.33)*	0.821 (0.41)**
MOBILE	NA	NA	NA	−0.452 (0.46)
WINDOW	NA	NA	NA	0.252 (0.226)
Constant	−0.683 (0.341)**	−0.907 (0.727)	−0.664 (0.506)	−0.785 (0.745)
rho	−0.095 (0.147)	0.163 (0.453)	0.049 (0.437)	0.182 (0.43)
N	320	249	250	246
Wald (χ^2)	46.39***	57.75***	55.09***	58.61 ***

Note: dep var = dependent variable. ***, **, * imply significance at 1%, 5%, and 10% levels respectively; numbers in parentheses are corresponding standard errors.
NA = The variables are not used in the models.

any type of window protection. The mean evacuation cost was about $200 per household.

Estimation Results

Tables 3 and 4 present the estimation results of the Heckman selection models using the Hurricane Ike survey and Hurricane Sandy survey, respectively. The dependent variable EVAC representing the risk preference (selection equation) and the dependent variable TIME representing time preference (regression equation) were jointly estimated. Four models with different control variables in each analysis were reported to demonstrate the robustness of the results. Overall, we found several significant factors consistent with some of the previous findings in the literature. In particular, past evacuation experience was the most important factor that influenced household evacuation behavior across all

Table 4. Estimation Results of Evacuation Time Decision for Hurricane Sandy

Variable name	Model 1	Model 2	Model 3	Model 4
Panel A (Dep var: TIME [Departure time of the evacuees])				
EXPERIENCE	2.626 (1.291)**	4.03 (2.003)**	4.715 (2.189)**	4.597 (2.081)**
ORDER	2.306 (2.159)	4.507 (3.213)	5.486 (3.568)	5.015 (3.402)
PLAN	−0.908 (0.833)	−0.875 (0.943)	−0.625 (1.018)	−0.718 (0.983)
PREPARE	1.916 (1.084)*	2.838 (1.432)**	3.137 (1.601)**	2.967 (1.521)*
INSURANCE	−1.337 (0.657)**	−1.393 (0.738)*	−1.562 (0.8)*	−1.55 (0.767)**
FLOOD	NA	NA	−0.151 (0.682)	−0.293 (0.682)
DAYS	0.227 (0.09)**	0.21 (0.085)**	0.183 (0.083)**	0.204 (0.085)**
INDEXP	0.003 (0.001)***	0.003 (0.001)***	0.002 (0.001)***	0.002 (0.001)***
HHSIZE	NA	NA	−0.56 (0.361)	−0.484 (0.348)
AGE	NA	0.032 (0.022)	0.032 (0.022)	0.038 (0.022)
GENDER	NA	−0.48 (0.72)	−0.489 (0.78)	−0.543 (0.75)
RACE	−1.395 (0.731)*	−1.722 (0.864)**	−2.135 (1.004)**	−1.88 (0.96)**
HEAD	NA	−0.869 (1.218)	−1.318 (1.364)	−1.26 (1.31)
DISABLES	NA	NA	NA	−0.817 (0.693)
SMOKE	3.906 (1.056)***	3.85 (1.221)***	3.641 (1.355)***	4.08 (1.308)***
YEARS	NA	NA	NA	−0.017 (0.018)
OWNER	1.696 (0.74)**	1.586 (0.745)**	1.363 (0.781)*	1.408 (0.773)*
VEHICLES	NA	NA	0.457 (0.376)	0.368 (0.364)
Constant	−6.183 (4.841)	−11.214 (6.807)	−12.729 (6.863)	−10.061 (6.615)
Panel B (Dep var: EVAC [Whether the respondent evacuated or not, yes = 1, no = 0])				
EXPERIENCE	0.845 (0.218)***	0.849 (0.218)***	0.833 (0.221)***	0.832 (0.221)***
ORDER	1.417 (0.165)***	1.416 (0.165)***	1.41 (0.167)***	1.41 (0.167)***
PLAN	0.11 (0.164)	0.106 (0.165)	0.102 (0.165)	0.108 (0.166)
PREPARE	0.518 (0.163)***	0.521 (0.163)***	0.517 (0.164)***	0.516 (0.164)***
INSURANCE	−0.031 (0.133)	−0.034 (0.133)	−0.033 (0.137)	−0.036 (0.138)
HHSIZE	NA	NA	−0.066 (0.055)	−0.065 (0.055)
GENDER	NA	0.043 (0.129)	0.047 (0.13)	0.047 (0.13)
RACE	−0.14 (0.155)	−0.142 (0.156)	−0.165 (0.158)	−0.164 (0.158)
SENIOR	0.189 (0.08)**	0.187 (0.08)**	0.17 (0.082)**	0.176 (0.084)**
HEAD	−0.324 (0.17)*	−0.324 (0.171)*	−0.349 (0.172)**	−0.354 (0.173)**
DISABLES	NA	NA	NA	−0.049 (0.125)
SMOKE	−0.182 (0.227)	−0.183 (0.227)	−0.2 (0.231)	−0.185 (0.234)
YEARS	NA	NA	NA	0 (0.003)
VEHICLES	NA	NA	0.007 (0.063)	0.006 (0.063)
WINDOW	NA	NA	0.036 (0.246)	0.037 (0.246)
Constant	−2.081 (0.264)***	−2.09 (0.266)***	−1.872 (0.359)***	−1.771 (0.436)***
P	1.818 (2.021)	3.813 (2.969)	4.846 (3.263)	4.351 (3.121)
N	1,211	1,211	1,211	1,211
Wald (χ^2)	58.44***	53.22***	48.96 ***	53.39***

Note: dep var = dependent variable. ***, **, * imply significance at 1%, 5%, and 10% levels respectively; numbers in parentheses are corresponding standard errors. NA = The variables are not used in the models.

models. Households with past evacuation experience were more likely to evacuate during Hurricane Ike and Sandy and were more likely to leave early for a safer location.

Specifically, estimation results in Table 3 (Panel B) indicate that Texas residents were more likely to evacuate if they had previous evacuation experience, supporting the positive role of past experiences found in the literature. Receiving mandatory or voluntary evacuation orders also increased the probability of evacuation. Risk perception indicators are found to motivate evacuation behaviors, as those who considered the risk of flooding were more likely to leave. However, households also perceive other types of risks during a hurricane event. For example, those who considered the probability of crime and looting were less likely to evacuate, which is consistent with earlier findings (*61*). Additionally, non-white respondents, female respondents, and homeowners were more likely to evacuate. Since evacuation activities require expenditures associated with food, lodging, and transportation, households who could not afford these costs might be reluctant to leave (*62*). A report covered by Florido (*63*) emphasized the findings by Behr's research team that a 7-day evacuation cost for a family of four without nearby relatives would be more than $2,000 for lodging, fuel, and food. We found evidence that the cost of evacuation negatively affected the probability of evacuation. Those who were laid off from work were also less likely to evacuate. The report (*63*) stated that people often thought they would lose their jobs if they chose to evacuate. We did not find evidence to show factors such as age, children, or mobile homes to be statistically significant factors on the evacuation decision.

On the other hand, estimation results in Table 3 (Panel A) indicate that among those who evacuated for Hurricane Ike, having past evacuation experience is still a strong predictor for early departure. Those who consider an evacuation order as important information are also the ones who evacuated in advance. As expected, prior experience and evacuation orders are consistently the most important drivers to influence household behavior. We also found that the number of days they would need to stay away from home and being a homeowner affected household decisions to leave early. This is possibly because households who already have a destination in mind are more likely to evacuate early. Those who planned to travel longer distances or stay longer away from home might also choose to leave early. Those who evacuated later rather than sooner were white respondents, those who indicated that they were influenced by neighbors, and those with higher evacuation expenditures. Consistent with the earlier studies (e.g., Mozumder and Vásquez [*64*]), the cost of evacuation was not only a barrier for people to evacuate, but also contributed to the delaying of their evacuation timing decisions. In line with suggestions made by Behr's research team in the report (*63*), people with the fewest means often wait till the last minute for evacuation and find the cheapest hotel rooms are gone, and the remaining ones are more expensive and farther away.

It is worth noting that although receiving evacuation orders increased the probability of evacuation, it insignificantly affected the timing of the evacuation. One possible explanation is that households who had past experience or planned to travel for more days had already left even before the evacuation order was issued. Therefore, receiving an evacuation order is not a strong factor in predicting the departure timing. On another note, household belief on the importance of the evacuation orders (IMORDER) was a strong driver to motivate early evacuation. Florido's report (*63*) emphasized that policies and messaging for risk communication are important since certain populations will not evacuate for fear of personal property and potential disruption to their medical regimen. Therefore, it is essential for local governments and emergency management agencies to have effective risk communication systems, provide more accurate information, forecasts and warnings to earn public trust, and enhance public awareness of the importance of the evacuation orders and compliance. In line with the suggestions by Mozumder and Vásquez (*28*), providing financial assistance can be an effective incentive to influence evacuation behavior, as the finding indicates that higher evacuation cost was associated with a lower probability of leaving as well as leaving at a later time.

According to Table 4 (Panel B), residents from Hurricane-Sandy-affected areas had a higher probability of evacuating if they had evacuated in the past, received evacuation orders, and made necessary preparation to leave home during an emergency. Senior households were more likely to evacuate, while household heads were less likely to leave. We did not find evidence to show other demographic factors, such as age, race, or gender, to be statistically significant. Similar to the results from Hurricane Ike, evacuation orders were not a statistically significant factor in explaining the timing of the evacuation decision (see Table 4, Panel A). Compared with Hurricane Ike, we found similar results for the factors influencing time preferences for Hurricane Sandy. Those who evacuated early before Sandy's landfall were associated with having past evacuation experience, days needed away from home, expenditure, and being a homeowner. We also found that households who made necessary preparedness for evacuation left early, but those who purchased insurance departed later. Households with insurance coverage might perceive a lower risk from the hurricane damage, and thus were reluctant to evacuate at an early time until they had to leave.

The parameter ρ in both Tables 3 and 4 is insignificant, indicating that there was no sample selection bias in our models. The unobserved factors affecting people's hurricane evacuation decisions are not correlated with the unobserved factors affecting their hurricane evacuation timing decision, thus rejecting our first hypothesis (H_1). Therefore, the findings can be used to understand household evacuation time preferences without separately identifying evacuees and non-evacuees. To check the robustness of our estimations, we ran the two-stage regression analyses expressed in Equations 3 and 4 separately. As shown in Table 5, the estimation results of evacuation time decision using the ordinary least squares (OLS) regression (see Model 2 and Model 4) and the estimation results of evacuation decision using the probit regression (see Model 1 and Model 3) are all consistent with those from Heckman selection models (compared with Model 4 from Table 3 and Model 4 from Table 4).

It is also important to notice that factors that influence evacuation decisions are not necessarily the same motivating factors for early or late evacuation. We are not arguing that early evacuation is absolutely better than a late evacuation, but understanding the factors on the timing decisions will provide important inputs for emergency management and evacuation planning during

Table 5. Robustness Check of the Heckman Selection Models for Hurricane Ike and Hurricane Sandy

Hurricane Ike			Hurricane Sandy		
Variable Name	Model 1 EVAC	Model 2 TIME	Variable Name	Model 3 EVAC	Model 4 TIME
EXPERIENCE	0.433 (0.207)**	0.423 (0.202)**	EXPERIENCE	0.827 (0.222)***	2.133 (0.805)***
DAYS	NA	0.046 (0.012)***	DAYS	NA	0.200 (0.103)*
INDEXP	−0.001 (0.000)***	−0.001 (0.000)**	INDEXP	NA	0.002 (0.001)***
RACE	−0.784 (0.273)***	−0.547 (0.213)**	RACE	−0.162 (0.158)	−1.350 (0.816)
AGE	0.009 (0.009)	−0.004 (0.008)	AGE	NA	0.022 (0.021)
GENDER	−0.477 (0.199)**	0.090 (0.180)	GENDER	0.051 (0.130)	−0.822 (0.685)
HHSIZE	−0.049 (0.090)	0.006 (0.075)	HHSIZE	−0.067 (0.055)	−0.210 (0.273)
OWNER	0.525 (0.365)	0.486 (0.319)	OWNER	NA	1.397 (0.884)
WINDOW	0.138 (0.193)	0.062 (0.175)	WINDOW	0.033 (0.247)	NA
LAIDOFF	−0.711 (0.301)**	NA	INSURANCE	−0.042 (0.138)	−1.478 (0.720)**
NEIGHBOR	−0.375 (0.302)	−0.501 (0.265)*	SMOKE	−0.189 (0.234)	4.642 (1.107)***
INCOME	NA	0.001 (0.032)	PREPARE	(0.164)	1.354 (0.848)
VOLUNTARY	0.873 (0.218)***	−0.101 (0.239)	ORDER	1.420 (0.167)***	0.486 (0.769)
MANDATORY	1.994 (0.259)***	0.271 (0.225)	PLAN	0.110 (0.166)	−1.018 (0.898)
IMPCRIME	−0.288 (0.201)	−0.049 (0.181)	HEAD	−0.368 (0.172)**	0.001 (0.864)
IMPSURGE	0.735 (0.211)***	0.097 (0.208)	VEHICLES	0.007 (0.063)	0.383 (0.330)
IMORDER	NA	0.310 (0.193)	FLOOD	NA	−0.303 (0.736)
IMPPETS	−0.337 (0.211)	−0.120 (0.205)	YEARS	−0.000 (0.003)	−0.018 (0.017)
EDUC	−0.047 (0.190)	−0.049 (0.180)	DISABLES	−0.052 (0.125)	−0.768 (0.652)
CHILDREN	−0.007 (0.293)	−0.211 (0.221)	SENIOR	0.178 (0.084)**	NA
MOBILE	−0.087 (0.414)	0.163 (0.354)	NA	NA	NA
Constant	−0.746 (0.672)	2.156 (0.630)***	Constant	−1.759 (0.436)***	−1.419 (2.374)
N	246	102	*N*	1,211	91
R-squared	0.382	0.448	*R*-squared	0.287	0.478

Note: ***, **, * imply significance at 1%, 5%, and 10% levels respectively; numbers in parentheses are corresponding standard errors. NA = The variables are not used in the models.

an approaching hurricane. Overall, results from both survey data sets indicate that the most important determinants of evacuation were prior evacuation experience, evacuation orders, and risk perceptions. On the other hand, the most important determinants of early evacuation were the prior evacuation experiences, days spent at the evacuation destination, and cost of evacuation. Socioeconomic factors, such as gender, race, seniority, and ownership, also influenced the two decisions, but these results are less consistent across the two groups of respondents. Results from both data sets supported both our second hypothesis (H_2), that past hurricane experience is a valid reference point for evacuation behavior, and the third hypothesis (H_3), that other household characteristics can also be important in explaining heterogeneous decision-making on whether to evacuate and when to evacuate.

Discussion and Conclusion

In the face of an approaching hurricane, many people demand to relocate within a short period of time. Under the same evacuation order, however, households are found to make different evacuation decisions, which can be driven by different levels of risk perception, social network, and individual characteristics. Shadow evacuation might also occur, as households outside the evacuation zone may find it necessary to evacuate. On the supply side, it has become increasingly important for emergency management agencies to design an efficient and safe evacuation plan, especially in large coastal metropolitan areas. If the evacuation process is not managed efficiently, it can do more harm as a result of traffic delays, crashes, and accidents, as well as mental and physical stress. As such, the timing of a household's evacuation is extremely important because it could improve or exacerbate the efficacy of overall evacuations.

In this paper, we developed a Heckman selection model for analyzing the evacuation timing decision of households during a hurricane event and predicted their evacuation behavior for future planning purposes. We used respondents' evacuation timing and a list of explanatory variables to estimate which factors play the key role in determining the timing of evacuation. Understanding the time-specific demand side and supply side of evacuation can make emergency management more effective.

We examined household behavior using two hurricane survey data sets, including one from Hurricane Ike where a relatively high evacuation rate (48%) was observed, and another one from Hurricane Sandy with a very low evacuation rate (only 8%). The differences in the evacuation rate were also associated with the differences in the proportion of respondents having past hurricane experiences (59% versus 4%) and the proportion of respondents who received evacuation orders (30% versus 8%). The empirical analyses further demonstrated this finding that past hurricane experience was a significant factor influencing the timing of evacuation behavior. While receiving an evacuation order increased the probability of evacuation, respondents were not influenced by it when deciding the timing of evacuation.

The insights and opinions of those organizations that were involved directly in the evacuations are critically important in understanding the factors that influence the evacuation behavior and also the timing of evacuation. *A Case Study of Hurricane Irma*, released by the Transportation Sustainability Research Center at UC Berkeley, reported similar results to ours (*65*). This study analyzed survey data from areas affected by Hurricane Irma using descriptive statistics and discrete choice models to investigate both evacuee and non-evacuee behavior. Their evacuation models produced similar results, such as the mandatory evacuation order and high-risk perceptions leading to an increased likelihood of evacuation. However, in reality, the FEMA administrator Long claimed that people in the path of a powerful hurricane had ignored evacuation orders and refused to evacuate even when they received the warnings at the local and state level (*63*). To convince as many people as possible to get out of harm's way before it is too late, emergency managers try to help residents visualize the impacts of potential storm surge and establish better risk communication. The Weather Channel featured the hurricane visualization tool and showed cars and debris floating by in the floodwaters (*63*). The National Institute of Standards and Technology (NIST) also conducted a project to investigate the role of emergency communications in hurricane evacuation decisions (*66*).

Wong et al. (*65*) also indicated that experience played a role in departure day and time, as people with prior hurricane experiences were more likely to be early evacuees for Hurricane Irma. However, several differences were also evident. For example, they found experience with at least one prior hurricane (and being a previous evacuee) decreased the likelihood of evacuation, which they thought may be a result of the unique characteristics of recent Florida hurricanes These results may be explained by the residents who have lived in storm-prone regions (i.e., Florida) for a long time and experienced many near misses perhaps assuming that the next storm will be more of the same, leading to the decision to stay rather than evacuate (*63*). However, our study indicated that previous hurricane experience increased evacuations from Hurricane Ike and Hurricane Sandy, which made landfall in areas different from Hurricane Irma's. The northeastern region of the U.S., affected by Hurricane Sandy, and the Gulf coast area of the U.S., affected by Hurricane Ike, have different geographic and demographic characteristics, and residents in both areas have different hurricane experiences. These findings imply that all national-level emergency agencies and community planners—such as the Department of Homeland Security (DHS), Department of Transportation (DOT), FEMA, National Weather Service (NWS), and U.S. Army Corps of Engineers (USACE)—should work closely with local- and state-level agencies, and collect, analyze, and monitor residents' evacuation behavior for the purpose of reducing casualties in vulnerable communities (*67*).

Future research should continue exploring different factors affecting both the evacuation decisions and the timing of evacuation. For example, modes of transport available would be an essential factor altering household decisions. Florido' report (*63*) argued that some households do not have the ability to evacuate because of unavailable modes of transport, according to Professor Wolshon. The northeastern regions of the U.S. affected by Hurricane Sandy rely heavily on public transit, so disruptions to transit services could become a barrier to evacuation. Travel modal options could also affect the decision on when people choose to leave. The difference between normal travel times and various delay times would be another factor that is worth investigating. While concerns for travel delays might be a barrier to evacuation, they might, in turn, be a motivator for early departure. While this study mainly focuses on the demand side of hurricane evacuations, future research should try to make connections on the supply side by seeking opinions from emergency agencies and community planners in coastal areas. The inputs from organizations that lead the evacuations added to the findings at the household level will ascertain additional nuances and insights.

In closing, this study contributed to the literature by adopting a different model from previous evacuation behavior studies. The Heckman selection models helped us predict more precisely what factors influence evacuation time among households affected by a destructive hurricane. Also, the non-presence of selection bias indicated that risk preferences and time preferences are not the same. Evacuation planners cannot simply rely on the factors influencing evacuation decisions to predict the timing of the evacuation made by households. It is essential to identify the key factors that determine peoples' time preferences for hurricane evacuation. Moreover, the Atlantic and Gulf coast areas have different geographic and demographic characteristics, and it is essential to apply empirical analysis across different locations to get a comparative perspective. Finally, we hope that the findings will be useful for emergency management and community planners in coastal areas that are frequently exposed to hurricane threats. The empirical analysis performed in this study provides insight into households' timing preferences in making evacuation decisions and can be applied to other hurricane events across different locations.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: Fan Jiang, Pallab Mozumder; data collection: Fan Jiang, Sisi Meng, Pallab Mozumder; analysis and interpretation of results: Fan Jiang, Sisi Meng, Nafisa Halim; draft manuscript preparation: Fan Jiang, Sisi Meng. All authors reviewed the results and approved the final version of the manuscript.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: We acknowledge the support from the National Science Foundation (Award #1832693 and # 2122135).

Data Accessibility Statement

Data will be made available on reasonable request subject to compliance with IRB guidelines.

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The authors are solely responsible for the findings in this paper.