Protection or Peril of Following the Crowd in a Pandemic-Concurrent Flood Evacuation

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Abstract: The decisions of whether and how to evacuate during a climate disaster are influenced by a wide range of factors, including emergency messaging, social influences, and sociodemographics. Further complexity is introduced when multiple hazards occur simultaneously, such as a flood evacuation taking place amid a viral pandemic that requires physical distancing. Such multihazard events can necessitate a nuanced navigation of competing decision-making strategies wherein a desire to follow peers is weighed against contagion risks. To better understand these trade-offs, we distributed an online survey during a COVID-19 pandemic surge in July 2020 to 600 individuals in three midwestern and three southern states in the United States with high risk of flooding. In this paper, we estimate a random parameter discrete choice model in both preference space and willingness-to-pay space. The results of our model show that the directionality and magnitude of the influence of peers' choices of whether and how to evacuate vary widely across respondents. Overall, the decision of *whether* to evacuate is positively impacted by peer behavior, while the decision of *how* to evacuate (i.e., ride-type selection) is negatively impacted by peer influence. Furthermore, an increase in flood threat level lessens the magnitude of peer impacts. In terms of the COVID-19 pandemic impacts, respondents who perceive it to be a major health risk are more reluctant to evacuate, but this effect is mitigated by increased flood threat level. These findings have important implications for the design of tailored emergency messaging strategies and the role of shared rides in multihazard evacuations. Specifically, emphasizing or deemphasizing the severity of each threat in a multihazard scenario may assist in: (1) encouraging a reprioritization of competing risk perceptions; and (2) magnifying or neutralizing the impacts of social influence, thereby (3) nudging evacuation decision-making toward a desired outcome. **DOI: 10.1061/(ASCE)NH.1527-6996.0000577.** *© 2022 American Society of Civil Engineers.*

Introduction

The novel coronavirus (COVID-19) pandemic has overlapped with numerous climate disasters in the United States, including floods, earthquakes, tornadoes, wildfires, and hurricanes (Smith 2021). Of all natural disasters worldwide, floods are the most common and destructive (Kellens et al. 2013; Oshiro et al. 2022), presenting evacuation-related challenges of road closures and impacts to critical infrastructure (Lim et al. 2013). Prior research has shown that evacuation decision-making is primarily influenced by access to resources, risk perception, and social influence (Dash and Gladwin 2007; Huang et al. 2012; Riad et al. 1999; Sadri et al. 2017b, 2021). However, this existing body of research has largely focused on single-hazard events, while a research gap persists pertaining to the study of evacuation decision-making in the context of multihazard disasters. In addition to the many major flooding events that have occurred during the pandemic, including in Germany and China (Simonovic et al. 2021), this study is motivated by a flood evacuation of over 11,000 individuals from parts of Midland, Michigan, and surrounding areas caused by the failure of two dams: the Edenville and downstream Sanford. This event occurred on May 19–20, 2020 while the state was under a pandemic stay-at-home mandate.

At the time of data collection, the total number of COVID-19 cases in the six states examined in this study ranged from 40,000 to 160,000, and the corresponding total number of deaths ranged from 800 to 7,500, as shown in Table 1. Challenges with large-scale evacuations during the pandemic include risk of contact, exposure, transmission, and cross-community spread of the virus due to difficulties maintaining recommended physical distancing while evacuating (Dargin et al. 2021). Epidemiological models have predicted hurricane evacuations during the pandemic to increase the number of COVID-19 cases, although this effect could be minimized through guidance of evacuees away from high risk and crowded areas (Pei et al. 2020). This research is timely as pandemic-concurrent evacuation strategies have stressed the importance of facilitating resource sharing among neighbors and reducing staying behaviors associated with viral exposure concerns (Wong et al. 2021).

In essence, dual climate and health hazards present contradictory strategies: sheltering-in-place to isolate oneself against viral exposure versus gathering with the masses on roads and in shelters to evade localized threats to life and property. Crowds are undesirable in both natural hazard emergencies and contagious health emergencies, and yet, social connectivity bolsters resilience to these same emergencies by providing access to material and immaterial resources. Therefore, it is difficult to predict what effect peer behavior will have on the decisions of whether and how to evacuate during a multihazard disaster.

The goal of this research is to better understand flood evacuation decision-making amid the viral COVID-19 pandemic to gain insights into the role of shared rides in multihazard evacuations.

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Table 1. COVID-19 statistics for July 2020 in surveyed US states

State	New cases	7-day average	New deaths	7-day average	Total cases	Total deaths	Order began	Order ended	Current status	Governor
Georgia	2,309	1,900	21	17	124,267	3,071	April 3, 2020	April 30, 2020	Reopening	Republican
Illinois	880	788	24	25	160,898	7,468	March 21, 2020	May 29, 2020	Reopening	Democrat
Louisiana	2,083	1,099	17	12	88,700	3,509	March 23, 2020	May 15, 2020	Pausing	Democrat
Michigan	429	367	5	12	80,759	6,358	March 24, 2020	June 1, 2020	Pausing	Democrat
Mississippi	652	639	9	10	40,829	1,332	April 3, 2020	April 27, 2020	Reopened	Republican
Wisconsin	584	522	1	4	44,181	841	March 25, 2020	May 13, 2020	Reopened	Democrat

Specifically, this study examines the following three research questions:

1. What is the impact of *social influence* on multihazard evacuation decision-making? Using the observation of peers' evacuation decisions as a proxy for social influence, we investigate its mixed impact (i.e., following versus avoiding) on evacuation decision-making, depending on the type of evacuation decision (i.e., whether or how to evacuate) within the dual emergency context (i.e., a pandemic-concurrent flooding event).
2. What is the impact of *flood threat level* on multihazard evacuation decision-making? For example, a more severe emergency may lead to assigning a lower (or higher) importance to peer influence. Our work investigates the heterogeneity in these peer effects.
3. What is the impact of *pandemic risk perception* on multihazard evacuation decision-making? Here we home in on the way decision makers navigate the competing role of flood threats and pandemic risks stemming from coexisting emergencies.

To investigate these questions, we collected survey data using a stated choice experiment to model hypothetical responses to a pandemic-concurrent flood evacuation. This web-based survey was distributed during a pandemic surge from June 30 to July 2, 2020, to 600 individuals in Illinois, Michigan, Wisconsin, Georgia, Louisiana, and Mississippi. Discrete choice models in willingness-to-pay space with random parameters are developed to control for heterogeneity in evacuation decisions.

This paper is organized as follows. The next section presents a literature review, followed by an overview of the data collection and experimental design. Then we present the discrete choice methodology and discuss the results. The final section concludes with the implications of the findings.

Literature Review

Evacuation Decision-Making: Ride Choice

The decision of *how* to evacuate is typically examined through studies on mode and ride selection. To improve multimodal evacuation plans, this growing body of research focuses on mode choice in evacuations, in particular hurricane evacuations of transportation-disadvantaged individuals, with mode alternatives including personal vehicles, number of vehicles, and nonhousehold modes, such as riding with others, bus and rail transit, special evacuation buses, and taxis (Bian 2017; Bian et al. 2019; Deka and Carnegie 2010; Sadri et al. 2014a; Wong et al. 2020b). Findings from this research show that the most common evacuation mode is driving private vehicles (Lindell et al. 2011; Wong et al. 2018) followed by riding with others (Bian et al. 2019). Evacuees using nonhousehold modes are most likely to evacuate by special evacuation buses (Sadri et al. 2014a), and transportation-disadvantaged evacuees rely more on public transit for evacuation (Deka and Carnegie 2010). The choice of evacuating by nonhousehold transportation modes (e.g., riding with others, buses, taxis, etc.) has been shown to be related to sociodemographics, household characteristics, evacuation experience, and destination type (Sadri et al. 2014a). Additional work has explored the joint nature of evacuation decision-making, confirming that mode choice is related to destination choice (Bian et al. 2019).

Recently, research has begun to consider the role of both commercial and community ridesharing for evacuation of individuals who lack access to personal vehicles. *Ridesharing* is defined as "the formal or informal sharing of rides between drivers and passengers with similar origin–destination pairings" (Shaheen and Cohen 2020; Shared and Digital Mobility Committee 2018). It is a new form of mobility that is currently of interest in alternative-mode evacuation planning due to its flexible, on-demand nature and its potential to reduce traffic, address the last-mile problem, and improve access to mobility resources for socially vulnerable populations who require transportation assistance, such as carless individuals. However, the use of ridesharing for emergency evacuation presents notable challenges, including driver willingness, safety, and liability, as well as the guarantee of equity protections for disadvantaged individuals as required by the Americans with Disabilities Act and Title VI of the Civil Rights Act (Westervelt et al. 2017).

Specifically, *single*-hazard evacuation research has found evidence of driver willingness to offer shared evacuation rides with strangers (Li et al. 2018; Wong and Shaheen 2019), but further research on *multi*hazard evacuation ride choice is warranted (Borowski et al. 2021). The current paper uses a discrete choice model to examine the decision of whether and how to evacuate in a multihazard scenario, while considering social and emotional factors, as well as communication and perceptions of relative threat and risk levels.

Risk Perception: Messaging and Emotionality

Literature reviews of disaster evacuation behavior show that risk perception is consistently a positive predictor of evacuation (Baker 1991; Thompson et al. 2017). Research on emergency messaging suggests that decision-making is impacted through six stages of communication: hearing, confirming, understanding, believing, personalizing, and responding (e.g., Mileti and O'Brien 1992; Mileti and Peek 2000; Mileti and Sorensen 1990). Beyond formal messaging, individuals often rely on social networks to gather information to support decision-making (Lindell et al. 2019). Research on the use of on-demand ridesourcing for evacuation has shown that this decision is influenced by the notification source and the level of urgency communicated (Borowski and Stathopoulos 2020). The message content, style, and receiver characteristics (such as social setting, social ties, social structure, psychological factors, and prewarning perceptions) can all impact decision-making and emergency response (Mileti and Peek 2000).

Emotional states have also been shown to have a significant effect on decision-making (Chorus et al. 2013; Gutteling et al. 2018;

Hess and Stathopoulos 2013; Lerner and Keltner 2000; Liu et al. 2017). Experiencing heightened emotions may lead to "hot-state" decision-making or impulsive actions in pursuit of one's visceral desires (Reid 2010). In the context of evacuations, it is likely that negative emotions will predominantly impact decision-making. The emotional content of messages can also affect decision-making, as observed for messages emphasizing impacts on buildings and property and those emphasizing impacts on human life, both of which have been found to have a positive effect on evacuation intention, risk perception, and response efficacy (Morss et al. 2018). The four primary negative emotions typically studied in decision-making research are fear, anger, sadness, and anxiety (Jin 2009; Jin et al. 2016; Kim and Cameron 2011; Lerner and Keltner 2000). It is important to note that although emotionality can impact decision-making, most of the research in this area has revealed that panicking is rarely observed during emergency events (Mileti and Peek 2000; Quarantelli 2001).

The present study advances this line of research by examining the impact of evacuation messaging with increasing threat levels on the decisions of whether and how to evacuate in a multihazard scenario. The present study specifically explores the impacts of *fear* and *anxiety* on evacuation decision-making in a multihazard scenario.

Social Influence and Peer Effects

The influence of social networks on evacuation decision-making is an ongoing area of research. It has been shown that families, relatives, friends, neighbors, and coworkers impact evacuation decision-making (Gladwin et al. 2007). Typically, familial relationships have a stronger influence on evacuation decisions than community relationships (Perry 1979). Several works account for the joint nature of evacuation decisions, such as the effect of social influence on evacuation decision-making within the context of household gatherings (Liu et al. 2014). Contagion-based network science analysis has been used to simulate the cascading impacts of family relationships (e.g., parents, siblings, relatives, etc.), as well as other social ties (e.g., neighbors, colleagues, friends, etc.), on evacuation decision-making and behavior (Hasan and Ukkusuri 2011).

Within the burgeoning area of research on social influence and evacuation decision-making, most prior studies have examined the effects of egocentric network characteristics on evacuation behavior (Ahmed et al. 2020; Gehlot et al. 2019; Sadri et al. 2015, 2017a, b). For a comprehensive review of social influence on evacuation decisions, please refer to Sadri et al. (2021), which recommends future research on new models for encouraging shared mobility during extreme events to address the question of under what conditions evacuees are willing to share a ride. The present study is among the first to explore this research gap by integrating individual risk perception and social influence, as well as the conditionality of sharing rides during extreme events by including both private and shared ride types in our evacuation choice experiment.

Sociodemographics and Attitudes

Literature reviews of disaster evacuation behavior show that the relationships between evacuation behavior and several sociodemographic indicators display a mix of positive and negative effects, including education, income, and homeownership (Thompson et al. 2017). The decision of *whether* to evacuate is typically found to be positively correlated with being female, having children at home, and education level, while being negatively correlated with age, household size, and homeownership (Huang et al. 2016). Additional behavioral factors influencing the decision of *whether* to evacuate include income, race, employment status, and duration of residence, in addition to prior disaster experience, perceptions of risk, self-efficacy, and communication (such as official warnings, environmental cues from storm conditions, and social influence or connectivity; Collins et al. 2018; Demuth et al. 2016; Huang et al. 2016; Lazo et al. 2015; Metaxa-Kakavouli et al. 2018; Pei et al. 2020). Finally, the limitation or constraint of being *unable* to evacuate is often related to income, race, disability, and health status (Renne et al. 2011). It is worth noting that most of the studies in this space focus on *single*-hazard evacuation scenarios, and while some sociodemographics have remained unchanged during the pandemic, such as race and gender, others may be heavily influenced by the pandemic, like income and employment (Pei et al. 2020).

Pandemic Impacts on Travel Behavior

The COVID-19 pandemic has had a distinct impact on travel behavior, including less time spent commuting (US Bureau of Labor Statistics 2021) and a decline in shared mode ridership, such as public transit, subways, and bike-sharing systems (Abdullah et al. 2020; De Vos 2020; Rahimi et al. 2021; Teixeira and Lopes 2020). Some research has begun to examine evacuation decision-making regarding whether to evacuate within the pandemic context. Recent *multi*hazard evacuation research has shown that the COVID-19 pandemic is impacting evacuation decision-making and reducing evacuation likelihood (Alam and Chakraborty 2021; Borowski et al. 2021; Collins et al. 2021). Findings suggest that pandemic concerns take precedence over flood concerns in a multihazard evacuation (Borowski et al. 2021; Botzen et al. 2021). Older individuals with greater vulnerability to COVID-19 are even more likely to stay behind during an evacuation (Botzen et al. 2021; Meng et al. 2020). This may be because the individuals at greatest risk of severe COVID-19 consequences are those 85 years of age and older, as well as those with underlying medical conditions, often correlated with age (Centers for Disease Control and Prevention 2020). Regarding evacuation *ridesharing* during the pandemic, significant determinants include traditional sociodemographic factors, such as being Black, female, or a parent, as well as less traditional factors related to the sociopolitical context of the pandemic, including being Republican or a millennial (Borowski et al. 2021).

These significant factors influencing travel behavior within the context of the pandemic, such as age and ridesharing attitudes, are expected to be relevant to the multihazard evacuation event examined in this research.

Data Collection: Stated Preference Survey

A survey including a choice experiment was carefully designed to determine multihazard evacuation preferences with a focus on social influence, emotional response, and risk perception to study this multihazard decision-making phenomenon. Fig. 1 outlines the survey content and structure. Although this research study was motivated by a real evacuation event, data was collected using a stated preference survey to parse out behavioral mechanisms and compare choice determinants that can be challenging to recall and articulate in revealed preference surveys, as well as to expand the geographic and sociopolitical context of our study. Despite many well-documented challenges (e.g., Hausman 2012; Wong et al. 2020a), the use of stated preference data is common for evacuation

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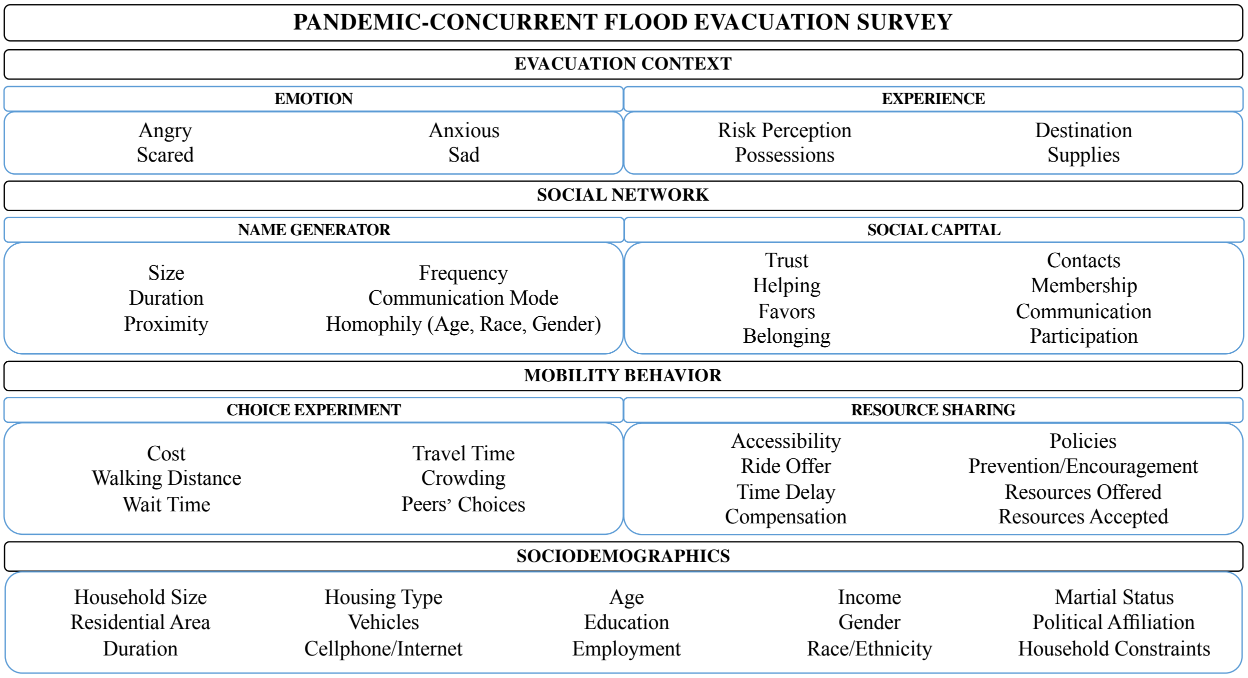

Fig. 1. Flow chart of pandemic-concurrent flood evacuation survey content.

mode-choice research (e.g., Bian et al. 2019; Sadri et al. 2014b). The survey was distributed online in three midwestern states (Illinois, Michigan, and Wisconsin) and three southern states (Georgia, Louisiana, and Mississippi) from June 30 to July 2, 2020. The selection of these six states was motivated by predictions of high flood risk according to authorities (National Oceanic and Atmospheric Administration 2020). Furthermore, each of the three states in each geographic region represents a different phase of pandemic restriction measures in July 2020 (i.e., reopened, reopening, and paused), as indicated in Table 1. The web-based survey was designed on Qualtrics and administered to 600 respondents using a Prolific respondent panel. After removing poor quality responses that failed an attention check question or showed patterns of inattentiveness, 586 respondents remained (98%). The survey contained roughly 75 questions, and the average length of time taken to complete the survey was 23 minutes. While online panels have been used extensively to conduct research during the COVID-19 pandemic (e.g., Parady et al. 2020), this data collection method has its limitations, such as representativeness of the sample demographics, which are summarized in the final section of this paper. The final survey instrument included the following five sections:

1. **Emotion.** In the first section, respondents were shown a description of the flood evacuation in Michigan that occurred in May 2020, including a quoted recollection of the flood evacuation experience of an evacuee as published in *The Guardian* (Holden 2020). This prompt was used to set the context and cognitively situate respondents in the emergency mindset and encourage preference learning (c.f., Araña and León 2008; Carlsson et al. 2012). Respondents were asked how likely they would be to feel various emotions in that evacuation situation (i.e., angry, scared, anxious, and sad) as measured along a five-point Likert-like scale, based on prior work by Borowski and Stathopoulos (2020). At the end of this section, respondents were asked how great of a threat to their personal health they believed it would be to evacuate during a COVID-19 outbreak (i.e., major, moderate, minor, or not a threat).
2. **Preevacuation questions.** Respondents were asked about evacuation logistics, such as how many belongings (i.e., movable possessions) they would take with them when evacuating, their household size, and where they would likely stay during a flood evacuation.
3. **Egocentric network name generator.** Respondents were asked to list up to five individuals in their life who they expect would provide the most support across four resource domains (i.e., material, instrumental, emotional, and informational) during a flood evacuation. This section also included questions about these relationships regarding distance, duration, frequency, and similarity in terms of gender, ethnicity, and age.
4. **Evacuation discrete choice experiment.** The most relevant section for the current paper is the choice experiment, which was designed following a pilot to identify attributes and levels, and using best practice methods for experimental design, including labeled alternatives, blocking, and Bayesian prior efficient design (Johnson et al. 2013; Lancsar and Louviere 2008; Rose and Bliemer 2009).
   a. **Context**. Participants were presented with nine hypothetical evacuation choice scenarios. The setup of every scenario was designed to anchor participants in the evacuation context: Respondents were shown a satellite map with a five-mile radius that they were told they would need to evacuate within two hours. Then for each successive choice scenario, they were given a gradually changing evacuation notification indicating an increasing flood threat level. A color-coded warning message was displayed above each scenario representing three flood threat levels (i.e., 3 "low" in green, 3 "moderate" in yellow, and 3 "extreme" in red), as shown in Figs. 2(a–c).
   b. **Alternatives.** Each of the nine scenarios presented three evacuation ride alternatives and the option to not evacuate (i.e., staying). Fig. 3 shows an example scenario. The "opt out" alternative, in this case "staying," is designed to increase realism and to capture a status quo effect instead of forcing an evacuation choice (e.g., Barton and Bergland 2010; Marsh et al. 2011; Meyerhoff and Liebe 2009). The three ride

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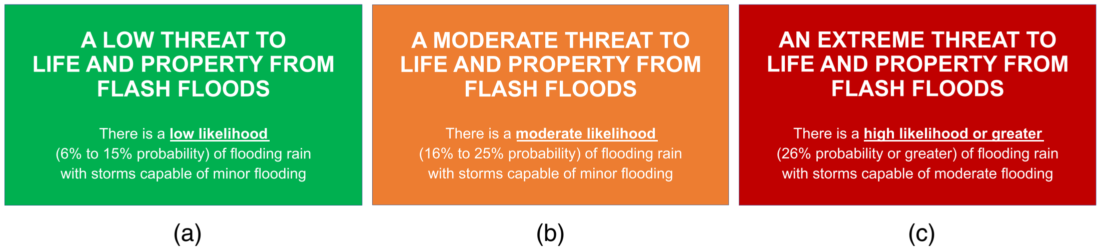

Fig. 2. Threat level context: (a) low; (b) moderate; and (c) extreme threat associated with evacuation scenarios.

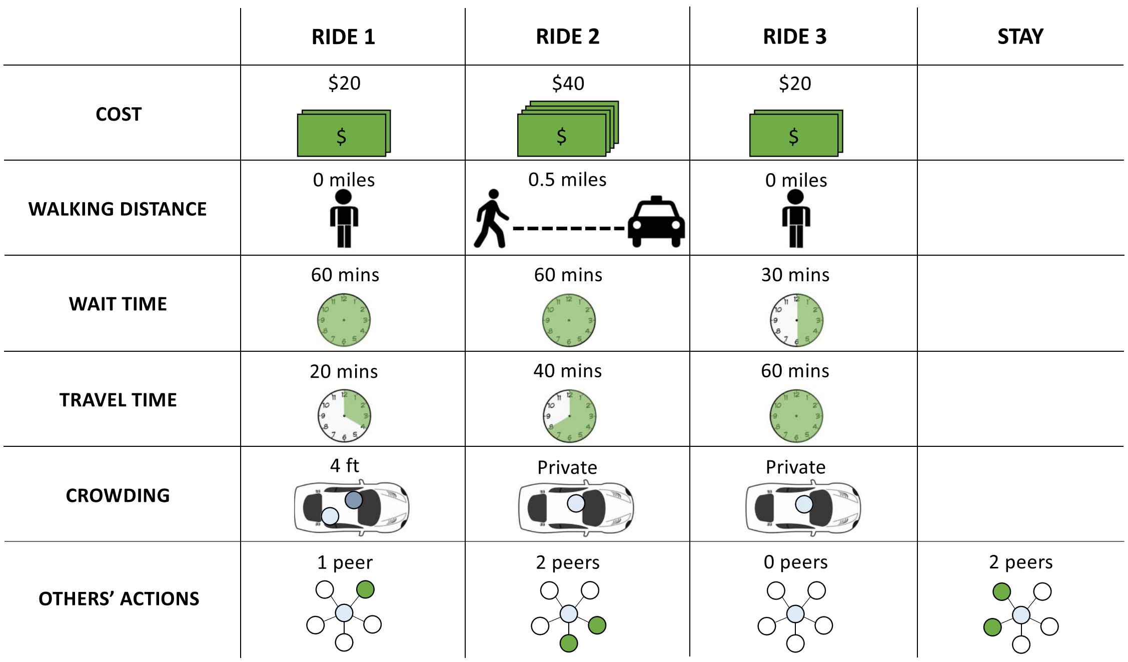

Fig. 3. Example of hypothetical evacuation choice scenario.

alternatives focus on community-based, grassroots ridesharing as opposed to commercial ride-hailing services.

c. **Attributes.** The experiment includes six attributes for the three ride types: ride cost, walking distance to the vehicle, wait time prior to travel, travel time to the destination, in-vehicle crowding (i.e., some rides were identified as "private," and others were shared with one stranger either in the front or back seat, wherein the distance between passengers was measured in feet), and peers' selections. To model peer effects, for all four evacuation alternatives, respondents were told what percentage of their egocentric social network selected each alternative. The egocentric social network data was collected as described in the third item of this list. This method of measuring social influence is novel and inspired by Gaker et al. (2010).

d. **Priors**. The attribute selection and presentation were qualitatively evaluated and then underwent pilot testing with respondents from Prolific ($n = 30$). Drawing on Bayesian priors from the pilot, an efficient Bayesian design was created using Ngene software (ChoiceMetrics 2012). Dominated and unrealistic scenarios were removed from the design before selecting the final set using the d-efficiency criterion.

e. **Blocking**. Twenty-seven scenarios were extracted to ensure attribute level balance and some degree of utility balance among scenarios. Using blocking in the Ngene design ensured a balanced splitting of three sets of nine scenarios (ChoiceMetrics 2012). Each respondent was randomly presented with one of the survey blocks to minimize fatigue.

5. **Sociodemographics.** Respondents were asked about their personal sociodemographics, as well as household constraints (such as living with one or more children under the age of 5, one or more adults of age 65 years or older, one or more pets, etc.). The survey sample sociodemographics are shown in Table 2.

Methodology

Random Parameter Model: Willingness-to-Pay Space

In discrete choice modeling, the standard utility parameterization occurs in preference space (Train 2009a). In this paper, we also specify our model in willingness-to-pay space wherein the coefficients directly represent the respondents' willingness to pay (Train and Weeks 2005). A benefit of this approach is its added flexibility in estimating random parameter distributions because willingness-to-pay parameters can take on any distribution chosen during the estimation.

Table 2. Survey sample sociodemographics

Category	Survey	Georgia	Illinois	Louisiana	Michigan	Mississippi	Wisconsin
Residence							
United States	—	3.2%	4.0%	1.4%	3.1%	0.9%	1.8%
Georgia	23.4%	—	—	—	—	—	—
Illinois	30.5%	—	—	—	—	—	—
Louisiana	7.1%	—	—	—	—	—	—
Michigan	15.9%	—	—	—	—	—	—
Mississippi	4.1%	—	—	—	—	—	—
Wisconsin	13.4%	—	—	—	—	—	—
Gender							
Male	46.3%	48.6%	49.1%	48.8%	49.0%	48.5%	49.4%
Female	51.9%	51.4%	50.9%	51.2%	51.0%	51.5%	50.6%
Other	1.0%	—	—	—	—	—	—
Age							
18–24	30.1%	9.9%	9.3%	9.4%	9.6%	10.2%	9.4%
25–34	31.4%	13.7%	13.9%	13.8%	12.9%	12.7%	12.7%
35–44	16.2%	13.3%	12.9%	12.6%	11.6%	12.8%	12.1%
45–54	11.9%	13.3%	12.8%	12.2%	12.9%	12.1%	12.7%
55–65	6.8%	12.2%	13.1%	12.9%	14.0%	12.8%	14.2%
65+	3.5%	13.8%	15.6%	15.5%	17.2%	15.9%	17.0%
Race							
White	65.0%	58.2%	71.7%	61.8%	78.3%	58.1%	85.3%
African American	14.5%	31.2%	13.8%	32.2%	13.6%	37.8%	6.3%
Asian	13.6%	4.1%	5.6%	1.6%	3.2%	0.9%	2.8%
American Indian	1.0%	0.2%	0.1%	0.5%	0.5%	0.4%	0.8%
Two or more	3.3%	2.2%	2.0%	2.0%	2.5%	1.4%	0.5%
Other	0.8%	2.5%	5.4%	1.2%	1.0%	0.9%	2.0%
Income							
<$10k	8.6%	11.1%	11.2%	11.9%	13.0%	12.6%	12.2%
$10k to $20k	8.8%	13.2%	11.5%	15.6%	13.4%	16.1%	11.3%
$20k to $30k	10.4%	15.6%	13.6%	16.1%	14.0%	16.6%	13.1%
$30k to $40k	7.8%	13.5%	12.3%	11.6%	13.4%	15.3%	14.0%
$40k to $50k	9.4%	10.4%	10.2%	10.6%	10.1%	12.0%	13.0%
$50k to $60k	9.8%	8.2%	8.8%	8.6%	8.4%	8.0%	10.2%
$60k to $80k	12.1%	11.1%	12.3%	11.1%	11.5%	9.5%	12.6%
$80k to $100k	8.8%	5.9%	7.1%	5.4%	6.2%	3.8%	5.9%
$100k to $120k	6.4%	3.8%	4.6%	3.4%	3.7%	2.4%	3.1%
$120k to $150k	6.3%	2.7%	3.3%	2.5%	2.7%	1.4%	2.0%
$150k to $200k	2.8%	2.1%	2.3%	1.5%	1.7%	1.0%	1.2%
>$200k	4.1%	2.4%	2.9%	1.6%	1.8%	1.3%	1.6%

The utility function U for individual n choosing alternative j for choice task t is given by

$$U_{njt} = \beta_n' x_{njt} + \varepsilon_{njt} \tag{1}$$

We can respecify this model so that the coefficient estimates directly represent the willingness-to-pay estimation. This provides an alternative to the standard practice of dividing nonprice attribute parameters by the price parameter to obtain the willingness-to-pay estimates. The advantage is that when willingness-to-pay estimates are directly defined for the parameter ratio, estimates are more tractable, plausible, and relevant for policy makers (dit Sourd et al. 2021; Mabit et al. 2006; Sonnier et al. 2007; Train and Weeks 2005). In our study, model parameters representing ride attributes, respondent sociodemographics, and attitudes are divided by the cost coefficient without creating issues in model estimation due to underlying scales or identification (Hensher 1994).

More formally, Eq. (1) can be rewritten to represent respondents' willingness to pay space following Scarpa et al. (2008) and Train and Weeks (2005), the only difference being that the price p is isolated from the nonprice evacuation ride attributes. Here coefficient λ_n is related to price and β' represents all other attributes

$$U_{njt} = -\lambda_n p_{njt} + \beta_n' x_{njt} + \varepsilon_{njt} \tag{2}$$

Continuing to follow Scarpa et al. (2008) and Train and Weeks (2005), given a scale parameter of μ where the error variance is expressed as $\mu_n^2(\pi^2/6)$, Eq. (2) can be divided by μ_n

$$U_{njt} = \left(\frac{-\lambda_n}{\mu_n}\right) p_{njt} + \left(\frac{\beta_n}{\mu_n}\right)' x_{njt} + \varepsilon_{njt} \tag{3}$$

Rewriting $(-\lambda_n/\mu_n) = \phi_n$ and $(\beta_n/\mu_n) = \xi_n$, and inserting into Eq. (2), we obtain

$$U_{njt} = \phi_n p_{njt} + \xi_n' x_{njt} + \varepsilon_{njt} \tag{4}$$

The calculation of willingness to pay based on the preference space model in Eq. (4) is executed as $z_n = (\xi_n/\phi_n)$and thereby $\xi_n = z_n \phi_n$. In practice, if we specified ϕ and ξ as randomly distributed parameters that vary over decision makers following a given distribution, the willingness-to-pay calculation needs to contend with two random terms that are not always jointly identified (Daly et al. 2012).

Reparameterizing Eq. (4) gives us the willingness-to-pay space model in Eq. (5). This model is behaviorally equivalent to the preference space specification in Eq. (4) (Train and Sonnier 2005), but the distribution of ϕ_n affects the estimation of willingness-to-pay values compared to Eq. (4). In particular, if we assume normal distributions, we may contend with highly skewed or unidentified moments of willingness to pay (Daly 2012)

$$U_{njt} = \phi_n p_{njt} + (z_n \phi_n)' x_{njt} + \varepsilon_{njt}$$
$$U_{njt} = \phi_n [p_{njt} + z_n' x_{njt}] + \varepsilon_{njt} \quad (5)$$

Indeed, many of the standard assumptions of random parameter distributions can lead to unidentified moments in the preference space form.

Random Parameters

Discrete choice models often include random parameters to account for taste heterogeneity across respondents by allowing these parameters to vary by individual, as detailed in Thiene and Scarpa (2009). A random parameter coefficient can be expressed as the sum of the population mean and the stochastic deviation representing each respondents' tastes, experiences, and uncertainty with that parameter while controlling for other effects in the model (Train 2009a). Applying this logic to our models of evacuation decision-making, we include random terms for price and peer effects in our preference space and willingness-to-pay space estimations, because we expect to find wide variation in these parameters across our sample population. A random parameter model is estimated here rather than other types of models that have been used to capture heterogeneity (e.g., Wong et al. 2020b) to facilitate comparison with many other evacuation studies that have employed this well-established method (e.g., Sadri et al. 2017b).

In our preference space model, *Cost* is specified as a random parameter with a log-normal distribution, which ensures a strictly negative sign, in line with many prior works (e.g., Hole and Kolstad 2012; Kjær et al. 2013; Matthews et al. 2017). After systematic testing, two additional random parameters are found to be significant for the social effect parameters: the *Share of Peers Staying* and the *Share of Peers Choosing a Ride*. These parameters are both defined as normally distributed to reflect the wide range of sensitivities associated with peer effects, spanning from avoiding to following behaviors (that is, the peer effect could produce either a positive or negative utility). Several interactions, including between *Peer Choice*, *Flood Threat*, and *Pandemic Risk Perception*, are also estimated in our models.

Model Estimations

For our data analysis, we first estimated a preference space model in order to identify for evacuation decision-making the significant fixed and random parameters, as well as interactions. After the preference space model estimation was complete, we specified the same model in willingness-to-pay space. We used the Apollo package for R (Hess and Palma 2019) to estimate the model in both spaces, employing the Broyden–Fletcher–Goldfarb–Shannon (BFGS) algorithm. For the random parameter estimation simulation, 1,000 Halton draws were found to produce stable parameter estimates. After comprehensive comparison, we found that the willingness-to-pay space formulation provides better fit and more plausible results.

Table 3 lists the significant variables that were included in the preference space and willingness-to-pay space model estimations. In our discussion, we will refer to the coefficients estimated in willingness-to-pay space, but we also include the preference space estimation for comparison and to highlight the improvement of fit obtained using willingness-to-pay estimation.

Methodological Equity Implications

It is worth noting that willingness-to-pay coefficients directly provide a *monetary equivalent worth* for each modeled parameter. For the decision of *how* to evacuate, our study examines shared rides and standard ride attributes, such as cost and travel time, and as such, the monetary value of ride attributes could have direct interpretations in the design of emergency ride-hailing services, including recommended discounts, promotions, and reimbursements. However, when employing the use of a willingness-to-pay analysis to study crisis scenarios like evacuations, it is extremely important to emphasize the need for governmental agencies to assist, protect, and provide free or very low-cost public resources to evacuees. The usefulness of willingness-to-pay space estimations for policy guidance is in using the utility to test hypotheses in "money space" (Thiene and Scarpa 2009), but it is crucial to note that *willingness* to pay is not the same as *ability* to pay. We wish to emphasize that the interpretation of our willingness-to-pay space estimations are intended to serve as a monetary equivalent worth or *perceived value* of behavior change and are *not* to be used as a recommendation to apply pricing or guide price setting.

Results

The results of the random parameter logit model estimated in preference space and willingness-to-pay space are shown in Table 4. The willingness-to-pay space estimation improves the fit compared to the preference space estimation with an increase in final log-likelihood of 220 and a higher adjusted rho squared. Three random parameters, twelve fixed parameters, and five interactions are included in the final model. All are significant to a 95% level of confidence or better except for the parameter *Pets*, which is insignificant in the willingness-to-pay estimation. The following subsections focus on the willingness-to-pay estimation results related to the random parameters for ride cost and social influence, as well as the fixed parameters for ride attributes, threat level, risk perception, and emotion.

Fixed Parameters

Ride Attributes

The flooding experiment included five mobility service attributes, in addition to the peer effect and threat level attributes discussed above and shown in Fig. 2. The willingness to pay for each of the ride attributes is shown in Fig. 4. Starting with the time attributes, for every additional minute of *Travel Time*, respondents would need to be compensated \$0.63 to accept a ride, while for every additional minute required to *Wait* for the evacuation ride to arrive, respondents would need to be compensated \$0.79. These findings suggest that the disutility of waiting time is 125% that of traveling time, meaning that waiting is perceived to be more costly than traveling time in an emergency. This reflects a similar asymmetry observed for nonemergency applications (Arentze and Molin 2013). For every additional mile required to *Walk* to access a ride during a flood evacuation, respondents need to be compensated \$32.78 to accept that ride, suggesting that walking is perceived as onerous in the emergency setting. This reflects prior research findings that the feasibility of walking during a flood evacuation is a function of water depth (Dias et al. 2021; Liu et al. 2009). To evacuate in the *Backseat* of a shared ride, respondents need to be compensated \$36.74, while evacuating in the *Front Seat* of a shared ride,

Nat. Hazards Rev., 2023, 24(1): 04022045

Table 3. Definitions of model variables

Model parameters	Variable	Definition	Minimum	Maximum	Mean	Standard deviation
Random parameters						
Cost	Count	Monetary cost of selecting evacuation ride	0	40	11.60	15.65
Peer fraction choosing ride	Count	Fraction of social network selecting a ride alternative (out of 5)	0	1	0.27	0.29
Peer fraction staying	Count	Fraction of social network selecting the stay alternative (out of 5)	0	0.8	0.19	0.22
Ride attributes						
Travel time	Count	Time of evacuation ride to travel from origin to destination	0	60	25.96	23.83
Wait time	Count	Time to wait until evacuation ride arrives	0	60	18.49	22.29
Walking distance	Count	Distance to walk to access evacuation ride	0	0.5	0.18	0.21
Shared back seat	Binary	Indicator of riding in the backseat in a shared evacuation ride with a stranger	0	1	0.05	0.22
Shared front seat	Binary	Indicator of riding in the front seat in a shared evacuation ride with a stranger	0	1	0.07	0.25
Threat level						
Extreme evacuation threat	Binary	Indicator of evacuation notification stating an extreme flood threat to life and property	0	1	0.33	0.47
Moderate evacuation threat	Binary	Indicator of evacuation notification stating a moderate flood threat to life and property	0	1	0.33	0.47
Sociodemographics						
Age	Categorical	Decade categories of respondent's age	1	6	2.44	1.37
Belongings	Count	One-tenth of pounds of luggage brought during evacuation	0	7.5	3.45	1.99
Disability	Binary	Indicator of respondent having a disability	0	1	0.03	0.16
Pets	Binary	Indicator of respondent living in a household with one or more pets	0	1	0.49	0.50
Attitudinal variables						
Evacuation anxiety	Likert scale	5-point level of evacuation anxiety	1	5	4.53	0.93
Evacuation fear	Likert scale	5-point level of evacuation fear	1	5	4.37	1.00
Major pandemic risk	Binary	Indicator of respondent viewing the pandemic as a major risk to their health	0	1	0.39	0.49

respondents need to be compensated at the lower monetary equivalent $27.72.

Risk Perception: Messaging and Emotionality

Risk perception is one of the key elements to understanding how households make decisions on whether to evacuate. Earlier work shows that risk is not perceived in the same way for all decision makers and may be influenced by social dimensions and the evacuation context (Dash and Gladwin 2007). Perceived flooding risk has been shown to be particularly important in a flooding evacuation context (Whitehead et al. 2000). Emotion has been shown to influence evacuation decision-making by impacting risk perception and message interpretation (DeYoung et al. 2019; Slovic and Peters 2006). While we are not specifically examining the impact of emotional states on risk perceptions in this study, our model results illustrate the impact of emotional states experienced by respondents on the willingness to pay to evacuate in a multihazard scenario.

Out of the four hypothesized emotional responses to the flooding evacuation storyline, only two were shown to be impactful, namely anxiety and fear. In terms of interpretation, for each additional level of *Evacuation Anxiety* likelihood (five-point scale), respondents need to be compensated $11.17 to evacuate. Instead, for each additional level of *Evacuation Fear* likelihood (five-point scale), respondents are willing to pay $14.74 to evacuate. The emotional states of anger and sadness were not found to be statistically significant in this model.

The survey also controlled for the role of COVID-19 pandemic contagion concerns in the form of a scale question. Results show that respondents who view the pandemic as a *Major Risk* to their health (binary variable) need to be compensated $219.45 to evacuate. There was no evidence of effects below the level of major risk (i.e., moderate, minor, or none), suggesting that a high threshold exists for pandemic risks in this evacuation setting. Once reached, however, the impact seems to surpass emotional effects. There is an important interaction effect between pandemic risk and flood threat communication. For each additional level of *Flood Threat* (4-point scale), the pandemic concern reduces by the equivalent amount of $85.02.

Sociodemographics

Willingness to pay as it relates to stay determinants is shown in Fig. 5. For every pound increase in *Evacuation Luggage*, respondents need to be compensated $4.36 to evacuate. For every additional ten years of *Age*, respondents need to be compensated $5.75. Respondents in households with one or more *Pets* need to be compensated $7.54. Respondents with a *Disability* need to be compensated $84.97. The magnitude of this value of willingness to pay is approximately 11 times greater than that for the other binary parameter, *Pets*, suggesting a greater severity of this evacuation constraint. While we cannot ascribe an attitudinal reason driving these behaviors, our findings may suggest key logistic challenges present in this evacuation context. In the course of specification testing, other factors, including gender, age, race/ethnicity,

Nat. Hazards Rev., 2023, 24(1): 04022045

Table 4. Random parameter logit model results

Model parameters	Preference space Estimate	Preference space Robust t-ratio	Preference space p-value	Willingness-to-pay space Estimate	Willingness-to-pay space Robust t-ratio	Willingness-to-pay space p-value
"Evacuate" alternative specific constant	4.22	8.64	0.000	4.20	8.61	0.000
"Stay" alternative specific constant	Fixed	—	—	Fixed	—	—
Random parameters						
Cost (mean)	−3.71	−36.44	0.000	−3.54	−46.50	0.000
Cost (standard deviation)	1.03	12.61	0.000	0.61	8.33	0.000
Share of peers choosing ride (mean)	−1.27	−5.10	0.000	71.77	6.45	0.000
Share of peers choosing ride (standard deviation)	−1.91	−12.70	0.000	57.29	8.80	0.000
Share of peers staying (mean)	7.76	9.33	0.000	−271.13	−8.03	0.000
Share of peers staying (standard deviation)	10.87	9.57	0.000	−57.81	−2.72	0.003
Ride attributes						
Travel time	−0.02	−11.61	0.000	0.63	8.31	0.000
Wait time	−0.03	−14.65	0.000	0.79	12.41	0.000
Walking distance	−1.08	−7.41	0.000	32.78	6.59	0.000
Shared ride (back seat)	−0.80	−10.03	0.000	36.74	8.86	0.000
Shared ride (front seat)	−0.84	−10.88	0.000	27.72	8.69	0.000
Sociodemographics						
Age	0.21	3.87	0.000	−5.75	−2.34	0.010
Evacuation luggage	0.10	2.46	0.007	−4.36	−2.62	0.004
Disability	1.13	2.55	0.005	−84.97	−2.49	0.006
Pets	0.43	2.68	0.004	−7.54	−1.36	0.087
Attitudinal variables						
Evacuation anxiety	0.37	2.97	0.002	−11.17	−2.09	0.018
Evacuation fear	−0.33	−2.87	0.002	14.74	3.37	0.000
Major pandemic risk perception	3.33	9.27	0.000	−219.45	−7.08	0.000
Interactions						
Peers choosing ride × moderate flood threat	0.50	1.79	0.037	−43.60	−4.09	0.000
Peers choosing ride × extreme flood threat	1.11	4.15	0.000	−72.81	−6.51	0.000
Peers staying × moderate flood threat	−9.27	−7.68	0.000	227.24	7.22	0.000
Peers staying × extreme flood threat	−21.13	−8.92	0.000	347.97	9.07	0.000
Flood threat × major pandemic risk perception	−1.48	−10.09	0.000	85.02	7.97	0.000
Model parameters						
Number of draws	1,000	—	—	1,000	—	—
Type of draws	Halton	—	—	Halton	—	—
Number of individuals	586	—	—	586	—	—
Number of modeled outcomes	5,274	—	—	5,274	—	—
Final log-likelihood	−5,645.22	—	—	−5,425.07	—	—
Adjusted rho-square	0.225	—	—	0.255	—	—
Coefficient of variation						
Cost	−0.277	—	—	−0.171	—	—
Share of peers choosing ride	1.501	—	—	0.798	—	—
Share of peers staying	1.402	—	—	0.213	—	—

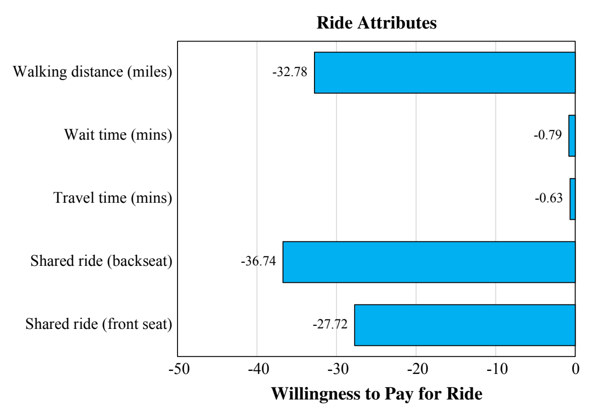

Fig. 4. Willingness to pay to select an evacuation ride type.

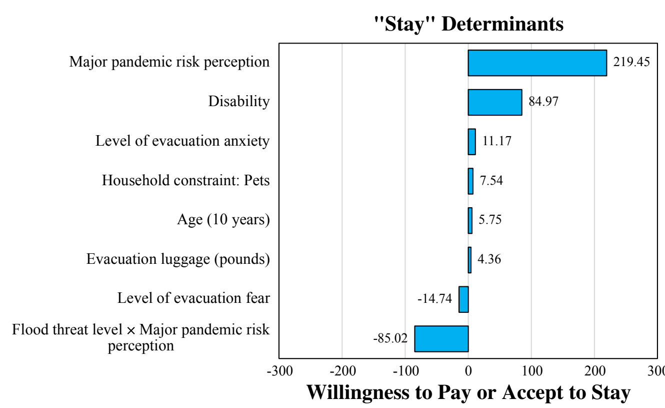

Fig. 5. Factors determining willlingness to pay or accept to stay.

median household income, homeownership, vehicle ownership, residential area type, political affiliation, and pandemic phase (i.e., reopened, reopening, and paused) were tested but resulted as being insignificant in the final model.

Random Parameters: Cost and Peer Effects

In the process of building our model, we opted to keep the random coefficients that had statistically significant standard deviations.

Nat. Hazards Rev., 2023, 24(1): 04022045

It is informative to compare the distribution of the random parameters in the two model structures. In the preference space estimation shown in Figs. 6(a–c), the cost parameter distribution is narrower with a coefficient of variation (COV) for *Cost* that is relatively small (0.28), while that for *Share of Peers Choosing a Ride* and *Share of Peers Staying* are both relatively large (1.50 and 1.40, respectively). This suggests low variance (or general agreement across respondents) regarding the impact of *Cost* on selecting a ride and instead high variance (or general disagreement across respondents) regarding the impact of the share of peers on the decisions of whether and how to evacuate.

The distributions of the random parameters in the willingness-to-pay space shown in Figs. 6(d–f) reveal less dispersion in each case (COV for *Cost* is 0.17, *Share of Peers Choosing a Ride* is 0.80, and *Share of Peers Staying* is 0.21). This suggests low variance in that the direct ratio estimation is better at capturing the heterogeneity in preferences for these factors, while we note that there is higher variance for the impact of *Share of Peers Choosing a Ride*.

In other words, in both models, respondents display the greatest diversity in their views of the benefits and risks associated with "following the crowd" in an evacuation setting.

Context of Flooding Threat

Willingness to pay levels out when it relates to social influence and flood threat as shown in Fig. 7. The strongest effects are observed for the *Share of Peers Staying* estimates. To aid interpretation, the results suggest that if the proportion of peers staying increases from 0% to 100%, respondents would require \$271.13 in compensation on average to go against their peers' decision to stay, which resembles earlier research findings on decision inertia across consecutive hurricane evacuation events (Murray-Tuite et al. 2012). This finding suggests a dominant effect of peer behavior when it comes to staying despite a flood warning. Comparing magnitudes for share of peers (Train 2009b), this coefficient is 3.7 times the magnitude of that for *Share of Peers Choosing a Ride*, suggesting a greater resistance to changing behavior related to staying compared to the

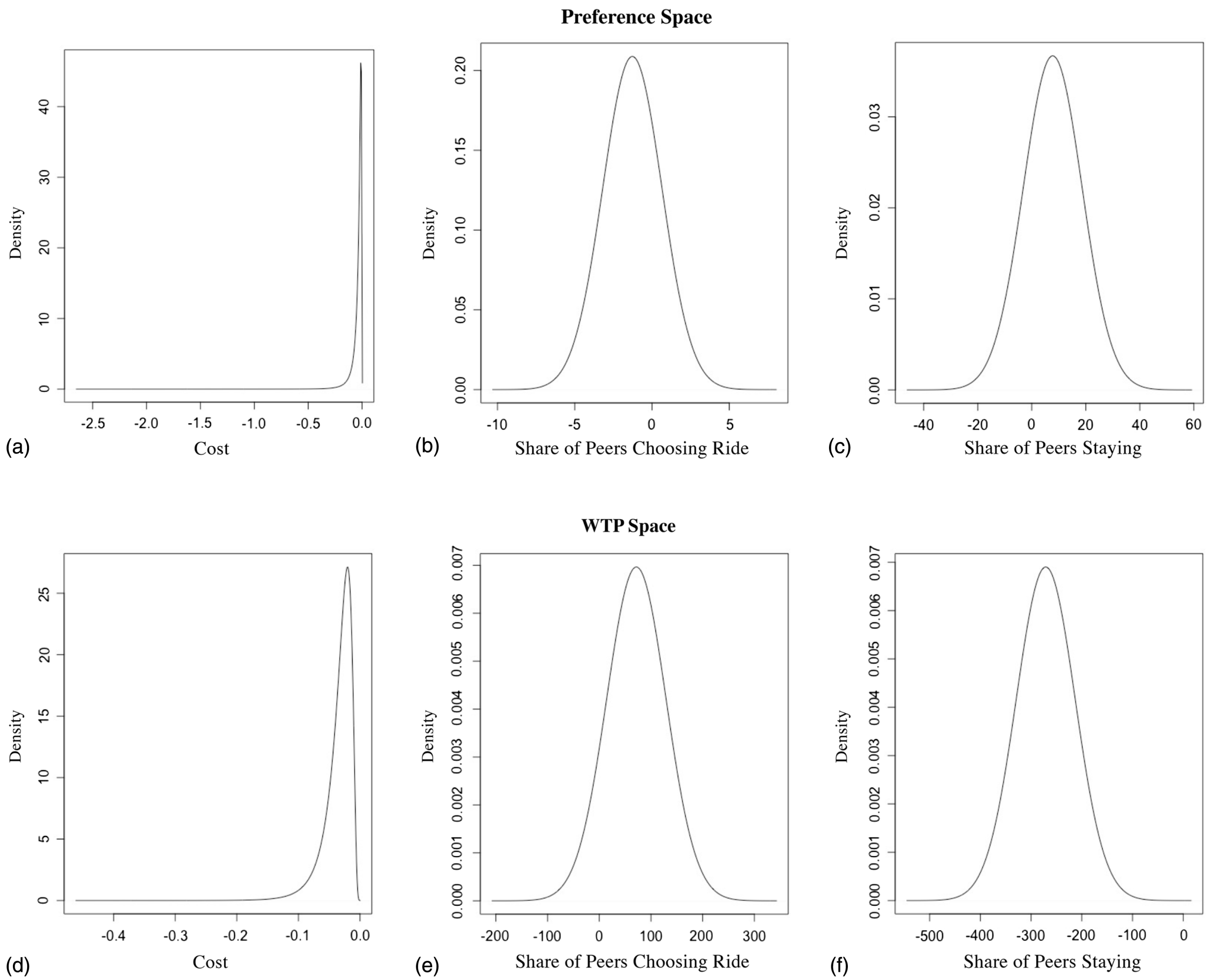

Fig. 6. Random parameter distributions for cost and social peer effects. Preference Space: Distribution of (a) *Cost* random parameter; (b) willingness to follow peers' evacuation *Ride* type selection; and (c) willingness to follow peers' decision to *Stay* during an evacuation across all draws. Willingness-to-pay space: Distribution of (d) *Cost* random parameter; (e) willingness to pay to follow peers' evacuation *Ride* type selection; and (f) willingness to pay to follow peers' decision to *Stay* during an evacuation across all draws.

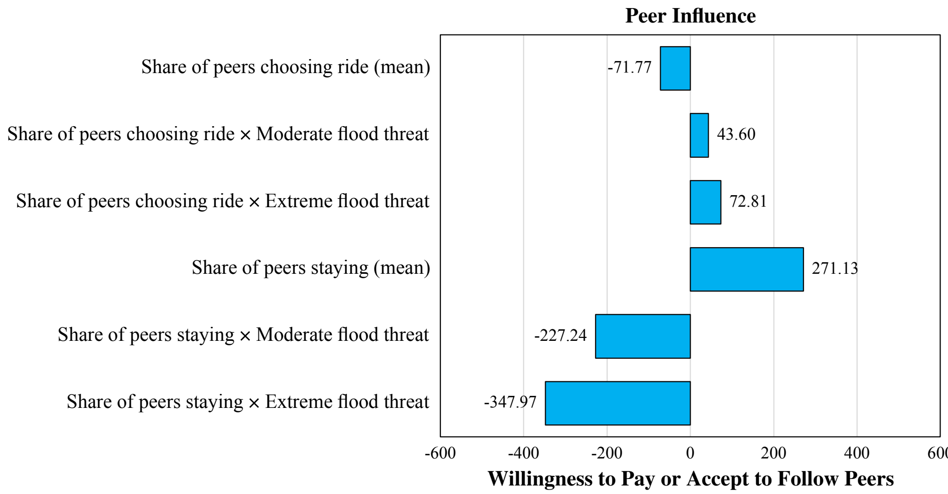

Fig. 7. Willingness to pay or accept to follow peers.

ride choice effect. The emergency context matters, however. When the *Flood Threat* is upgraded to moderate, this willingness-to-pay amount decreases to \$43.89 (i.e., \$271.13–\$227.24), and when *Flood Threat* is extreme, this amount switches sign, expressing a willingness to pay of \$76.84 (i.e., \$271.13–\$347.97) to evacuate. Overall, we note that the findings from our discrete choice model suggest that the impacts of the *Flood Threat* interactions with *Share of Peers Staying* are about five times greater than those with *Share of Peers Choosing a Ride* (that is, selecting one of three available ride types), suggesting that the impact of flood threat communication on the decision of *whether* to evacuate is greater than on the decision of *how* to evacuate.

Looking at the evacuation ride choice, the finding can be interpreted as follows: if the *Share of Peers Choosing a Ride* increases from 0% to 100%, respondents would be willing to pay an additional \$71.77 on average to go against their peers. When the *Flood Threat* is elevated to moderate, this amount decreases to \$28.17 (i.e., \$71.77–\$43.60), and when *Flood Threat* is extreme, this amount instead suggests a need to be compensated \$1.04 (i.e., \$71.77–\$72.81) to go against their peers.

Discussion

Nuanced Impact of "Following the Crowd"

Prior research on single-hazard evacuation scenarios suggests that social influence tends to result in a follow-the-crowd mentality (Sadri et al. 2021). This may be due to the sense of safety-in-numbers that the act of following others could provide (Lindell et al. 2005). However, in a multihazard scenario that involves both a climate and public health crisis, it is unclear whether a similar effect of social influence would be observed. In this type of multihazard event, the emergency messaging tends to be contradictory. Specifically, the advice provided for one crisis suggests staying home (the pandemic), while the advice for the other crisis suggests evacuating (flooding).

Our findings show that although the impact of social influence differs widely across respondents, overall, it is *negative* for ride selection and *positive* for the decision to stay. In other words, if more peers choose to stay despite official flood warnings, the respondent will be more likely to stay as well. Instead, if more peers choose a given evacuation ride type, respondents will be more likely to choose a different ride option. This makes sense given the pandemic-related advice to shelter-in-place and to follow social distancing protocol when leaving one's home.

When interacting social influence with flood threat messaging, an important observation can be made. When the threat communication is upgraded, evacuation scenarios with greater flood threat result in reduced impacts of social influence. That is, for the decision to stay, the original mean value of the need to be compensated to go against peers' decision to stay (i.e., \$271.13) is reduced by 84% with moderate flood risk and switches to a willingness to pay to evacuate in scenarios with extreme flood risk. This indicates that flood risk communication seems to supersede the reliance on following crowd cues, at least for severe evacuation events.

For ride selection, the original willingness to pay \$71.77 to go against peers' ride choice is reduced by 61% in scenarios with moderate flood threat and switches to a minimal need to be compensated to go against peers' ride selection in scenarios with extreme flood threat. This increased desire to follow peers' ride selection in evacuation scenarios with greater threat of flood risk may be related to perceiving the consequences of selecting an ineffective (e.g., overcrowded) evacuation ride type as being more severe.

The magnitude of the impact of the share of peers staying is 3.8 times greater than that of the share of peers choosing a ride, although the magnitude of the standard deviation for each is approximately equivalent. This asymmetry of social influence may be related to the signaling effect of visible peer behavior. The evacuation behavior of others could provide an environmental cue emphasizing the urgency of the scenario. When individuals evacuate, this behavior is more visible than their decision to stay and could result in a springing into action that motivates others to evacuate as well.

Dueling Risk Perceptions and Emotions

Our findings show that different emotional reactions lead to contrasting effects. For every level of increased evacuation anxiety, respondents would need to be compensated \$11.17 to evacuate. By contrast, for every level of increased evacuation fear, respondents are willing to pay \$14.74 to evacuate. One possible explanation for these divergent findings is that anxiety may lead to a "freeze" response, while fear may lead to a "flee" response. The impact of fear is greater in magnitude than the impact of anxiety by 32%.

This research also offers insight on the tension between pandemic concerns that suggest avoiding exposure introduced by evacuating in shared vehicles and flooding destruction that impels respondents to leave. Respondents who view the pandemic as a major risk to their health require high levels of compensation to evacuate, but for every increase of flood threat level, that amount reduces notably. Given the three levels of flood threat in the experiment (i.e., low, moderate, and extreme), this reduction could be so great as to entirely counterbalance the effect of pandemic risk evaluation. In practical terms, this suggests that respondents who view the pandemic as a major threat could demonstrate a willingness to pay to evacuate if the flood threat was great enough.

Practical Applications

This paper examines the effects of factors like social influence and emotion on evacuation decision-making during a simultaneous viral pandemic and flooding event. In terms of social influence, our results show that if more of an individual's peers choose to stay behind in this evacuation context, that individual is more likely to stay behind, as well. However, when evacuating, if more of an individual's peers choose a specific ride type, that individual is more likely to select a different type of evacuation ride. While peers' choices have a significant effect on evacuation decision-making, the severity of the flooding threat is shown to mitigate these peer effects. In terms of emotion, this study reveals that feelings of fear are more likely to result in the decision to evacuate, while feelings of anxiety are more likely to result in the decision to stay behind. Together these findings suggest that to nudge individuals toward the advised response regardless of peers' behavior, multihazard emergency communication should: (1) clearly emphasize the severity of the more threatening of the multiple hazards; and (2) carefully take into consideration the emotional impact of the messaging, for example, by bringing focus to self-efficacy and away from numerous hypothetical outcomes.

Summary and Conclusion

In this paper, we use a discrete choice model to analyze the decisions of whether and how to evacuate during a flooding disaster occurring simultaneously with the global COVID-19 health emergency. The focus of the analysis is on social influence and how it is affected by emergency messaging, emotionality, and the overlapping hazard setting. This problem is challenging given that the multihazard setting will likely necessitate a nuanced navigation of competing decision-making strategies wherein a desire to follow peers is weighed against contagion risks.

Drawing on data from a stated choice experiment, we report the results of a random parameter logit model in willingness-to-pay space. We examine the decision of whether to evacuate or stay behind in response to a flooding event. The modeling approach offers flexibility in assessing both unobserved and systematic heterogeneity present in evacuation responses. The critical takeaway from this research is that social influence during a multihazard evacuation event has vastly different impacts depending on the decision being made, threat levels, and taste heterogeneity. Overall, our findings show that social influence has a positive impact on *whether* one evacuates (i.e., stay versus go) and a negative impact on *how* one evacuates (i.e., evacuation ride-type choice). As flood threat increases, the magnitude of the effect of social influence decreases. Large taste heterogeneity across respondents regarding the impact of social influence is observed. Finally, some emotional states are found to be significantly correlated with evacuation decision-making, but only fear and anxiety. Specifically, evacuation anxiety is positively correlated with the decision to stay, while evacuation fear is positively correlated with the decision to evacuate.

Policy Implications for Emergency Communication

Pandemic-concurrent evacuation decision-making can be nudged in different directions by emphasizing different hazard components and their associated threat levels, which can impact the magnitude of the social influence effect. Peer behavior is largely outside of the control of emergency communication management, but some behaviors could be broadcasted and amplified, such as communicating the fact that others are evacuating. There is an inherent asymmetric signaling effect that occurs during multihazard evacuations, likely due to the decision to evacuate being more visible to others compared to the decision to stay, which suggests a potential two-pronged approach to communicating peer behavior via both formal and informal channels. Communication strategies should utilize risk perception, emotion, and behavioral broadcasting carefully to intentionally nudge evacuation decision-making toward the desired outcome.

Limitations

There are three main limitations to this work. First, some biases exist in the sampling frame. There is a sampling bias or demographic imbalance in the survey sample that is skewed toward individuals under the age of 45, those who are Asian, and those of higher income. This is due in part to using convenience-based sampling, which is justified for evacuation research (e.g., Wong et al. 2020b) and COVID-19-era travel behavior studies (e.g., Parady et al. 2020) due to safety concerns. Second, the results were found using a stated preference choice experiment, which presents the risk of hypothetical bias occurring when respondents lack experience with the situation they are being asked to consider. This has been shown to result in upward-biased, overstated, or inflated willingness-to-pay values, as well as large variation in responses (Hausman 2012; Hensher 2010; Wong et al. 2020a). Attempting to mitigate this bias, we employed a technique of using a quoted recollection to situate respondents in the emergency context. This piloted approach is experimental, because the best method for achieving this effect is currently unknown, and more research is needed to determine the best approach to addressing biases in evacuation experiments. As such, we encourage further investigation into data collection methods, including experiential games and virtual reality. Finally, in this exploratory work, the emotion variables (i.e., anxiety and fear) were each measured using a single survey question and modeled as continuous variables, while more accurately, emotion should be treated as a latent factor using multiple indicators. Future work should extend the analysis of the impact of emotion on multihazard evacuation decision-making by treating it as a latent variable.

Data Availability Statement

The survey data that support the findings of this study are not publicly available due to protection of human subjects. Data with appropriate protection is available on request from the corresponding author.

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References

Abdullah, M., C. Dias, D. Muley, and M. Shahin. 2020. "Exploring the impacts of COVID-19 on travel behavior and mode preferences." *Transp. Res. Interdiscip. Perspect.* 8 (Mar): 100255. https://doi.org/10.1016/j.trip.2020.100255.

Ahmed, M. A., A. M. Sadri, and M. Hadi. 2020. "Modeling social network influence on hurricane evacuation decision consistency and sharing capacity." *Transp. Res. Interdiscip. Perspect.* 7 (14): 100180. https://doi.org/10.1016/j.trip.2020.100180.

Alam, M. S., and T. Chakraborty. 2021. "Understanding the nexus between public risk perception of COVID-19 and evacuation behavior during cyclone Amphan in Bangladesh." *Heliyon* 7 (7): e07655. https://doi.org/10.1016/j.heliyon.2021.e07655.

Araña, J. E., and C. J. León. 2008. "Do emotions matter? Coherent preferences under anchoring and emotional effects." *Ecol. Econ.* 66 (4): 700–711. https://doi.org/10.1016/j.ecolecon.2007.11.005.

Arentze, T. A., and E. J. E. Molin. 2013. "Travelers' preferences in multimodal networks: Design and results of a comprehensive series of choice experiments." *Transp. Res. Part A Policy Pract.* 58 (Sep): 15–28. https://doi.org/10.1016/j.tra.2013.10.005.

Baker, E. J. 1991. "Hurricane evacuation behavior." *Int. J. Mass Emerg. Disasters* 9 (2): 287–310.

Barton, D. N., and O. Bergland. 2010. "Valuing irrigation water using a choice experiment: An 'individual status quo' modelling of farm specific water scarcity." *Environ. Dev. Econ.* 15 (3): 321–340. https://doi.org/10.1017/S1355770X10000045.

Bian, R. 2017. "Development of a mode and destination type joint choice model for hurricane evacuation." ProQuest dissertations & theses, Agricultural and Mechanical College, Louisiana State Univ.

Bian, R., C. G. Wilmot, R. Gudishala, and E. J. Baker. 2019. "Modeling household-level hurricane evacuation mode and destination type joint choice using data from multiple post-storm behavioral surveys." *Transp. Res. Part C Emerging Technol.* 99 (Mar): 130–143. https://doi.org/10.1016/j.trc.2019.01.009.

Borowski, E., V. L. Cedillo, and A. Stathopoulos. 2021. "Dueling emergencies: Flood evacuation ridesharing during the COVID-19 pandemic." *Transp. Res. Interdiscip. Perspect.* 10 (Mar): 100352. https://doi.org/10.1016/j.trip.2021.100352.

Borowski, E., and A. Stathopoulos. 2020. "On-demand ridesourcing for urban emergency evacuation events: An exploration of message content, emotionality, and intersectionality." *Int. J. Disaster Risk Reduct.* 44 (2): 101406. https://doi.org/10.1016/j.ijdrr.2019.101406.

Botzen, W. J., J. M. Mol, P. J. Robinson, J. Zhang, and J. Czajkowski. 2021. "Individual hurricane evacuation intentions during the COVID-19 pandemic: Insights for risk communication and emergency management policies." *Nat. Hazard.* 2021 (Jan): 1–16. https://doi.org/10.1007/s11069-021-05064-2.

Carlsson, F., M. R. Mørkbak, and S. B. Olsen. 2012. "The first time is the hardest: A test of ordering effects in choice experiments." *J. Choice Modell.* 5 (2): 19–37. https://doi.org/10.1016/S1755-5345(13)70051-4.

Centers for Disease Control and Prevention. 2020. "People at increased risk: And other people who need to take extra precautions." Accessed July 1, 2020. https://www.cdc.gov/coronavirus/2019-ncov/need-extra-precautions/index.html.

ChoiceMetrics. 2012. *Ngene 1.1.1 User manual & reference guide*. Sydney, Australia: ChoiceMetrics.

Chorus, C. G., M. J. Koetse, and A. Hoen. 2013. "Consumer preferences for alternative fuel vehicles: Comparing a utility maximization and a regret minimization model." *Energy Policy* 2013 (1): 901–908. https://doi.org/10.1016/j.enpol.2013.06.064.

Collins, J., R. Ersing, A. Polen, M. Saunders, and J. Senkbeil. 2018. "The effects of social connections on evacuation decision making during Hurricane Irma." *Weather Clim. Soc.* 10 (12): 459–469. https://doi.org/10.1175/WCAS-D-17-0119.1.

Collins, J., A. Polen, K. McSweeney, D. Colón-Burgos, and I. Jernigan. 2021. "Hurricane risk perceptions and evacuation decision-making in the age of COVID-19." *Bull. Am. Meteorol. Soc.* 102 (4): 836–848. https://doi.org/10.1175/BAMS-D-20-0229.1.

Daly, A., S. Hess, and K. Train. 2012. "Assuring finite moments for willingness to pay in random coefficient models." *Transportation* 39 (1): 19–31. https://doi.org/10.1007/s11116-011-9331-3.

Dargin, J. S., Q. Li, G. Jawer, X. Xiao, and A. Mostafavi. 2021. "Compound hazards: An examination of how hurricane protective actions could increase transmission risk of COVID-19." *Int. J. Disaster Risk Reduct.* 65 (Apr): 102560. https://doi.org/10.1016/j.ijdrr.2021.102560.

Dash, N., and H. Gladwin. 2007. "Evacuation decision making and behavioral responses: Individual and household." *Nat. Hazard. Rev.* 8 (3): 69–77. https://doi.org/10.1061/(ASCE)1527-6988(2007)8:3(69).

Deka, D., and J. Carnegie. 2010. "Analyzing evacuation behavior of transportation-disadvantaged populations in Northern New Jersey." In *Proc., Transportation Research Board 89th Annual Meeting Transportation Research Board*. Washington, DC: Transportation Research Board.

Demuth, J. L., R. E. Morss, J. K. Lazo, and C. Trumbo. 2016. "The effects of past hurricane experiences on evacuation intentions through risk perception and efficacy beliefs: A mediation analysis." *Weather Clim. Soc.* 8 (6): 327–344. https://doi.org/10.1175/WCAS-D-15-0074.1.

De Vos, J. 2020. "The effect of COVID-19 and subsequent social distancing on travel behavior." *Transp. Res. Interdiscip. Perspect.* 5 (Dec): 100121. https://doi.org/10.1016/j.trip.2020.100121.

DeYoung, S. E., J. N. Sutton, A. K. Farmer, D. Neal, and K. A. Nichols. 2019. "Death was not in the agenda for the day: Emotions, behavioral reactions, and perceptions in response to the 2018 Hawaii wireless emergency alert." *Int. J. Disaster Risk Reduct.* 36 (12): 101078. https://doi.org/10.1016/j.ijdrr.2019.101078.

Dias, C., N. Abd Rahman, and A. Zaiter. 2021. "Evacuation under flooded conditions: Experimental investigation of the influence of water depth on walking behaviors." *Int. J. Disaster Risk Reduct.* 58 (Oct): 102192. https://doi.org/10.1016/j.ijdrr.2021.102192.

dit Sourd, R. C., O. Beaumais, P. A. Mahieu, P. Martínez-Camblor, and R. Scarpa. 2021. "A contingent valuation test for measuring the construct validity of willingness-to-pay estimates derived from choice-experiments." *Land Econ.* 97 (3): 608–625.

Gaker, D., Y. Zheng, and J. Walker. 2010. "Experimental economics in transportation: Focus on social influences and provision of information." *Transp. Res. Rec.* 2156 (1): 47–55. https://doi.org/10.3141/2156-06.

Gehlot, H., A. M. Sadri, and S. V. Ukkusuri. 2019. "Joint modeling of evacuation departure and travel times in hurricanes." *Transportation* 46 (6): 2419–2440. https://doi.org/10.1007/s11116-018-9958-4.

Gladwin, H., J. K. Lazo, B. H. Morrow, W. G. Peacock, and H. E. Willoughby. 2007. "Social science research needs for the hurricane forecast and warning system." *Nat. Hazard. Rev.* 8 (3): 87–95. https://doi.org/10.1061/(ASCE)1527-6988(2007)8:3(87).

Gutteling, J. M., T. Terpstra, and J. H. Kerstholt. 2018. "Citizens' adaptive or avoiding behavioral response to an emergency message on their mobile phone." *J. Risk Res.* 21 (12): 1579–1591. https://doi.org/10.1080/13669877.2017.1351477.

Hasan, S., and S. V. Ukkusuri. 2011. "A threshold model of social contagion process for evacuation decision making." *Transp. Res. Part B Methodol.* 45 (7): 1590–1605. https://doi.org/10.1016/j.trb.2011.07.008.

Hausman, J. 2012. "Contingent valuation: From dubious to hopeless." *J. Econ. Perspect.* 26 (4): 43–56. https://doi.org/10.1257/jep.26.4.43.

Hensher, D. A. 1994. "Stated preference analysis of travel choices: The state of practice." *Transportation* 21 (2): 107–133. https://doi.org/10.1007/BF01098788.

Hensher, D. A. 2010. "Hypothetical bias, choice experiments and willingness to pay." *Transp. Res. Part B Methodol.* 44 (6): 735–752. https://doi.org/10.1016/j.trb.2009.12.012.

Hess, S., and D. Palma. 2019. "Apollo: A flexible, powerful and customisable freeware package for choice model estimation and application." *J. Choice Modell.* 2019 (1): 32. https://doi.org/10.1016/j.jocm.2019.100170.

Hess, S., and A. Stathopoulos. 2013. "A mixed random utility—Random regret model linking the choice of decision rule to latent character traits." *J. Choice Modell.* 9 (13): 27–38. https://doi.org/10.1016/j.jocm.2013.12.005.

Holden, E. 2020. "Michigan: Thousands evacuated after 'catastrophic' dam failures." Accessed May 20, 2020. https://www.theguardian.com/us-news/2020/may/20/michigan-dams-break-thousands-evacuated-floods.

Hole, A. R., and J. R. Kolstad. 2012. "Mixed logit estimation of willingness to pay distributions: A comparison of models in preference and WTP space using data from a health-related choice experiment." *Empirical Econ.* 42 (2): 445–469. https://doi.org/10.1007/s00181-011-0500-1.

Huang, S. K., M. K. Lindell, and C. S. Prater. 2016. "Who leaves and who stays? A review and statistical meta-analysis of hurricane evacuation studies." *Environ. Behav.* 48 (8): 991–1029. https://doi.org/10.1177/0013916515578485.

Huang, S. K., M. K. Lindell, C. S. Prater, H. C. Wu, and L. K. Siebeneck. 2012. "Household evacuation decision making in response to Hurricane Ike." *Nat. Hazard. Rev.* 13 (4): 283–296. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000074.

Jin, Y. 2009. "The effects of public's cognitive appraisal of emotions in crises on crisis coping and strategy assessment." *Public Relat. Rev.* 35 (Aug): 310–313. https://doi.org/10.1016/j.pubrev.2009.02.003.

Jin, Y., J. D. Fraustino, and B. F. Liu. 2016. "The scared, the outraged, and the anxious: How crisis emotions, involvement, and demographics predict publics' conative coping." *Int. J. Strategies Commun.* 10 (4): 289–308. https://doi.org/10.1080/1553118X.2016.1160401.

Johnson, F. R., E. Lancsar, D. Marshall, V. Kilambi, A. Mühlbacher, D. A. Regier, B. W. Bresnahan, B. Kanninen, and J. F. Bridges. 2013. "Constructing experimental designs for discrete-choice experiments: Report of the ISPOR conjoint analysis experimental design good research practices task force." *Value Health* 16 (1): 3–13. https://doi.org/10.1016/j.jval.2012.08.2223.

Kellens, W., T. Terpstra, and P. De Maeyer. 2013. "Perception and communication of flood risks: A systematic review of empirical research." *Risk Anal. Int. J.* 33 (1): 24–49. https://doi.org/10.1111/j.1539-6924.2012.01844.x.

Kim, H. J., and G. T. Cameron. 2011. "Emotions matter in crisis: The role of anger and sadness in the publics' response to crisis news framing and corporate crisis response." *Commun. Res.* 38 (6): 826–855. https://doi.org/10.1177/0093650210385813.

Kjær, T., M. Bech, C. Kronborg, and M. R. Mørkbak. 2013. "Public preferences for establishing nephrology facilities in Greenland: Estimating willingness-to-pay using a discrete choice experiment." *Eur. J. Health Econ.* 14 (5): 739–748. https://doi.org/10.1007/s10198-012-0418-3.

Lancsar, E., and J. Louviere. 2008. "Conducting discrete choice experiments to inform healthcare decision making." *Pharmacoeconomics* 26 (8): 661–677. https://doi.org/10.2165/00019053-200826080-00004.

Lazo, J. K., A. Bostrom, R. E. Morss, J. L. Demuth, and H. Lazrus. 2015. "Factors affecting hurricane evacuation intentions: Factors affecting hurricane evacuation intentions." *Risk Anal.* 35 (12): 1837–1857. https://doi.org/10.1111/risa.12407.

Lerner, J. S., and D. Keltner. 2000. "Beyond valence: Toward a model of emotion–specific influences on judgement and choice." *Cognit. Emot.* 14 (4): 473–493. https://doi.org/10.1080/026999300402763.

Li, M., J. Xu, X. Liu, C. Sun, and Z. Duan. 2018. "Use of shared-mobility services to accomplish emergency evacuation in urban areas via reduction in intermediate trips—Case study in Xi'an, China." *Sustainability* 10 (4862): 1–27. https://doi.org/10.3390/su10124862.

Lim, H., M. B. Lim, and M. Piantanakulchai. 2013. "A review of recent studies on flood evacuation planning." *J. Eastern Asia Soc. Transp. Studies* 10 (Jan): 147–162.

Lindell, M. K., S. Arlikatti, and S. K. Huang. 2019. "Immediate behavioral response to the June 17, 2013 flash floods in Uttarakhand, North India." *Int. J. Disaster Risk Reduct.* 34 (12): 129–146. https://doi.org/10.1016/j.ijdrr.2018.11.011.

Lindell, M. K., J. E. Kang, and C. S. Prater. 2011. "The logistics of household hurricane evacuation." *Nat. Hazard.* 58 (3): 1093–1109. https://doi.org/10.1007/s11069-011-9715-x.

Lindell, M. K., J. C. Lu, and C. S. Prater. 2005. "Household decision making and evacuation in response to Hurricane Lili." *Nat. Hazard. Rev.* 6 (4): 171–179. https://doi.org/10.1061/(ASCE)1527-6988(2005)6:4(171).

Liu, B. F., M. M. Wood, M. Egnoto, H. Bean, J. Sutton, D. S. Mileti, and S. Madden. 2017. "Is a picture worth a thousand words? the effects of maps and warning messages on how publics respond to disaster information." *Public Relat. Rev.* 43 (12): 493–506. https://doi.org/10.1016/j.pubrev.2017.04.004.

Liu, S., P. Murray-Tuite, and L. Schweitzer. 2014. "Incorporating household gathering and mode decisions in large-scale no-notice evacuation modeling." *Comput.-Aided Civ. Infrastruct. Eng.* 29 (2): 107–122.

Liu, Y., N. Okada, D. Shen, and S. Li. 2009. "Agent-based flood evacuation simulation of life-threatening conditions using vitae system model." *J. Nat. Disaster Sci.* 31 (2): 69–77. https://doi.org/10.2328/jnds.31.69.

Mabit, S. L., S. Caussade, and S. Hess. 2006. "Representation of taste heterogeneity in willingness to pay indicators using parameterization in willingness to pay space." In *Proc., European Transport Conf. 2006*. London: Association for European Transport. http://abstracts.aetransport.org/conference/index/id/12.

Marsh, D., L. Mkwara, and R. Scarpa. 2011. "Do respondents' perceptions of the status quo matter in non-market valuation with choice experiments? An application to New Zealand freshwater streams." *Sustainability* 3 (9): 1593–1615. https://doi.org/10.3390/su3091593.

Matthews, Y., R. Scarpa, and D. Marsh. 2017. "Stability of willingness-to-pay for coastal management: A choice experiment across three time periods." *Ecol. Econ.* 138 (Mar): 64–73. https://doi.org/10.1016/j.ecolecon.2017.03.031.

Meng, Y., et al. 2020. "Sex-specific clinical characteristics and prognosis of coronavirus disease-19 infection in Wuhan, China: A retrospective study of 168 severe patients." *PLoS Pathog.* 16 (4): e1008520. https://doi.org/10.1371/journal.ppat.1008520.

Metaxa-Kakavouli, D., P. Maas, and D. P. Aldrich. 2018. "How social ties influence hurricane evacuation behavior." In *Proc., ACM Human-Computer Interact*, 1–16. New York: Association for Computing Machinery.

Meyerhoff, J., and U. Liebe. 2009. "Status quo effect in choice experiments: Empirical evidence on attitudes and choice task complexity." *Land Econ.* 85 (3): 515–528.

Mileti, D. S., and P. W. O'Brien. 1992. "Warnings during disaster: Normalizing communicated risk." *Soc. Probl.* 39 (1): 40–57. https://doi.org/10.2307/3096912.

Mileti, D. S., and L. Peek. 2000. "The social psychology of public response to warnings of a nuclear power plant accident." *J. Hazard. Mater.* 75 (5): 181–194. https://doi.org/10.1016/S0304-3894(00)00179-5.

Mileti, D. S., and J. Sorensen. 1990. *Communication of emergency public warnings: A social science perspective and state-of-the-art assessment*. Oak Ridge, TN: Oak Ridge National Lab.

Morss, R. E., C. L. Cuite, J. L. Demuth, W. K. Hallman, and R. L. Shwom. 2018. "Is storm surge scary? The influence of hazard, impact, and fear-based messages and individual differences on responses to hurricane risks in the USA." *Int. J. Disaster Risk Reduct.* 30 (Jan): 44–58. https://doi.org/10.1016/j.ijdrr.2018.01.023.

Murray-Tuite, P., W. Yin, S. V. Ukkusuri, and H. Gladwin. 2012. "Changes in evacuation decisions between Hurricanes Ivan and Katrina." *Transp. Res. Rec.* 2312 (1): 98–107. https://doi.org/10.3141/2312-10.

National Oceanic and Atmospheric Administration. 2020. "U.S. Spring Outlook forecasts another year of widespread river flooding." Accessed June 26, 2020. https://www.noaa.gov/media-release/us-spring-outlook-forecasts-another-year-of-widespread-river-flooding.

Oshiro, K., Y. Tanioka, J. Schweizer, K. Zafren, H. Brugger, and P. Paal. 2022. "Prevention of hypothermia in the aftermath of natural disasters in areas at risk of avalanches, earthquakes, tsunamis and floods." *Int. J. Environ. Res. Public Health* 19 (3): 1098. https://doi.org/10.3390/ijerph19031098.

Parady, G., A. Taniguchi, and K. Takami. 2020. "Travel behavior changes during the COVID-19 pandemic in Japan: Analyzing the effects of risk perception and social influence on going-out self-restriction." *Transport. Res. Interdiscip. Perspect.* 7 (12): 100181. https://doi.org/10.1016/j.trip.2020.100181.

Pei, S., K. A. Dahl, T. K. Yamana, R. Licker, and J. Shaman. 2020. "Compound risks of hurricane evacuation amid the COVID-19 pandemic in the United States." *GeoHealth* 4 (12): e2020GH000319.

Perry, R. W. 1979. "Evacuation decision-making in natural disasters." *Mass Emerg.* 4 (Apr): 25–38.

Quarantelli, E. L. 2001. "Sociology of panic." *Univ. Delaware Disaster Res. Center* 28 (3): 1–12.

Rahimi, E., R. Shabanpour, A. Shamshiripour, and A. K. Mohammadian. 2021. "Perceived risk of using shared mobility services during the COVID-19 pandemic." *Transp. Res. Part F Psychol. Behav.* 81: 271–281. https://doi.org/10.1016/j.trf.2021.06.012.

Reid, A. 2010. "Hot-state decision making: Understanding consumer emotion and rationality." Accessed May 1, 2020. http://www.sentientdecisionscience.com/hot-state-decision-making-understanding-consumer-emotion-and-rationality/.

Renne, J. L., T. W. Sanchez, and T. Litman. 2011. "Carless and special needs evacuation planning: A literature review." *J. Plann. Lit.* 26 (4): 420–431. https://doi.org/10.1177/0885412211412315.

Riad, J. K., F. H. Norris, and R. B. Ruback. 1999. "Predicting evacuation in two major disasters: Risk perception, social influence, and access to resources 1." *J. Appl. Soc. Psychol.* 29 (5): 918–934. https://doi.org/10.1111/j.1559-1816.1999.tb00132.x.

Rose, J. M., and M. C. Bliemer. 2009. "Constructing efficient stated choice experimental designs." *Transp. Rev.* 29 (5): 587–617. https://doi.org/10.1080/01441640902827623.

Sadri, A. M., S. V. Ukkusuri, and M. A. Ahmed. 2021. "Review of social influence in crisis communications and evacuation decision-making." *Transp. Res. Interdiscip. Perspect.* 9 (Dec): 100325. https://doi.org/10.1016/j.trip.2021.100325.

Sadri, A. M., S. V. Ukkusuri, and H. Gladwin. 2015. "Social network influence on evacuation behavior: The case of hurricane sandy." In *Proc., 14th Int. Conf. on Travel Behaviour Research*. Leeds, UK: Univ. of Leeds.

Sadri, A. M., S. V. Ukkusuri, and H. Gladwin. 2017a. "Modeling joint evacuation decisions in social networks: The case of Hurricane Sandy." *J. Choice Modell.* 25 (Feb): 50–60. https://doi.org/10.1016/j.jocm.2017.02.002.

Sadri, A. M., S. V. Ukkusuri, and H. Gladwin. 2017b. "The role of social networks and information sources on hurricane evacuation decision making." *Nat. Hazard. Rev.* 18 (3): 04017005. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000244.

Sadri, A. M., S. V. Ukkusuri, P. Murray-Tuite, and H. Gladwin. 2014a. "Analysis of hurricane evacuee mode choice behavior." *Transp. Res. Part C Emerging Technol.* 48 (Aug): 37–46. https://doi.org/10.1016/j.trc.2014.08.008.

Sadri, A. M., S. V. Ukkusuri, P. Murray-Tuite, and H. Gladwin. 2014b. "How to evacuate: Model for understanding the routing strategies during hurricane evacuation." *J. Transp. Eng.* 140 (1): 61–69. https://doi.org/10.1061/(ASCE)TE.1943-5436.0000613.

Scarpa, R., M. Thiene, and K. Train. 2008. "Utility in willingness to pay space: A tool to address confounding random scale effects in destination choice to the Alps." *Am. J. Agric. Econ.* 90 (4): 994–1010. https://doi.org/10.1111/j.1467-8276.2008.01155.x.

Shaheen, S., and A. Cohen. 2020. "Mobility on demand in the United States." In *Analytics for the sharing economy: Mathematics engineering and business perspectives*, 225–227. Berkeley, CA: UC Berkeley. https://doi.org/10.1007/978-3-030-35032-1_14.

Shared and Digital Mobility Committee. 2018. "Taxonomy and definitions for terms related to shared mobility and enabling technologies." In *Shared and digital mobility committee*. Warrendale, PA: SAE International.

Simonovic, S. P., Z. W. Kundzewicz, and N. Wright. 2021. "Floods and the COVID-19 pandemic—A new double hazard problem." *Wiley Interdiscip. Rev.: Water* 8 (2): e1509. https://doi.org/10.1002/wat2.1509.

Slovic, P., and E. Peters. 2006. "Risk perception and affect." *Curr. Direct. Psychol. Sci.* 15 (6): 322–325. https://doi.org/10.1111/j.1467-8721.2006.00461.x.

Smith, A. B. 2021. "2020 U.S. billion-dollar weather and climate disasters in historical context." Accessed January 8, 2021. https://www.climate.gov/news-features/blogs/beyond-data/2020-us-billion-dollar-weather-and-climate-disasters-historical.

Sonnier, G., A. Ainslie, and T. Otter. 2007. "Heterogeneity distributions of willingness-to-pay in choice models." *Quant. Marketing Econ.* 5 (3): 313–331. https://doi.org/10.1007/s11129-007-9024-6.

Teixeira, J. F., and M. Lopes. 2020. "The link between bike sharing and subway use during the COVID-19 pandemic: The case-study of New York's Citi Bike." *Transp. Res. Interdiscip. Perspect.* 6 (12): 100166. https://doi.org/10.1016/j.trip.2020.100166.

Thiene, M., and R. Scarpa. 2009. "Deriving and testing efficient estimates of WTP distributions in destination choice models." *Environ. Resour. Econ.* 44 (3): 379–395. https://doi.org/10.1007/s10640-009-9291-7.

Thompson, R. R., D. R. Garfin, and R. C. Silver. 2017. "Evacuation from natural disasters: A systematic review of the literature." *Risk Anal.* 37 (4): 812–839. https://doi.org/10.1111/risa.12654.

Train, K., and G. Sonnier. 2005. "Mixed logit with bounded distributions of correlated partworths." In *Applications of simulation methods in environmental and resource economics*, 117–134. Berlin: Springer.

Train, K., and M. Weeks. 2005. "Discrete choice models in preference space and willingness-to-pay space." In *Applications of simulation methods in environmental and resource economics*, 1–16. Berlin: Springer.

Train, K. E. 2009a. *Discrete choice methods with simulation*. 2nd ed. New York: Cambridge University Press.

Train, K. E. 2009b. "Logit." In *Discrete choice methods with simulation*. Cambridge, UK: Cambridge University Press.

US Bureau of Labor Statistics. 2021. "American time use survey summary." Accessed November 1, 2021. https://www.bls.gov/news.release/atus.nr0.htm.

Westervelt, M., J. Schank, and E. Huang. 2017. "Partnerships with technology-enabled mobility companies: Lessons learned." *Transp. Res. Rec.* 2649 (1): 106–112. https://doi.org/10.3141/2649-12.

Whitehead, J. C., B. Edwards, M. Van Willigen, J. R. Maiolo, K. Wilson, and K. T. Smith. 2000. "Heading for higher ground: Factors affecting real and hypothetical hurricane evacuation behavior." *Global Environ. Change Part B: Environ. Hazards* 2 (4): 133–142. https://doi.org/10.1016/S1464-2867(01)00013-4.

Wong, S., J. Broader, A. Cohen, and S. Shaheen. 2021. "Double the trouble: A playbook for COVID-19 and evacuations." Accessed March 1, 2021. https://escholarship.org/uc/item/3dm9q8db.

Wong, S., and S. Shaheen. 2019. *Current state of the sharing economy and evacuations: Lessons from California*. Berkeley, CA: Univ. of California Institute of Transportation Studies. https://doi.org/10.7922/G2WW7FVK.

Wong, S., S. Shaheen, and J. Walker. 2018. *Understanding evacuee behavior: A case study of hurricane Irma*. Berkeley, CA: Univ. of California Institute of Transportation Studies.

Wong, S. D., C. G. Chorus, S. A. Shaheen, and J. L. Walker. 2020a. "A revealed preference methodology to evaluate regret minimization with challenging choice sets: A wildfire evacuation case study." *Travel Behav. Soc.* 20 (Apr): 331–347. https://doi.org/10.1016/j.tbs.2020.04.003.

Wong, S. D., A. J. Pel, S. A. Shaheen, and C. G. Chorus. 2020b. "Fleeing from Hurricane Irma: Empirical analysis of evacuation behavior using discrete choice theory." *Transp. Res. Part D Transp. Environ.* 79 (Dec): 102227. https://doi.org/10.1016/j.trd.2020.102227.