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ABSTRACT
Recent technological improvements have expanded the sharing economy (e.g., Airbnb, Lyft, and Uber), coinciding with a growing need for evacuation resources. To understand factors that influence sharing willingness in evacuations, we employed a multi-modeling approach using three model types: 1) four binary logit models that capture sharing scenario separately; 2) a portfolio choice model (PCM) that estimates dimensional dependency, and 3) a multi-choice latent class choice model (LCCM) that jointly estimates multiple scenarios via latent classes. We tested our approach by employing online survey data from Hurricane Irma (2017) evacuees (n=368). The multi-model approach uncovered behavioral nuances undetectable with one model. For example, the multi-choice LCCM and PCM models uncovered scenario correlation and the multi-choice LCCM found three classes – transportation sharers, adverse sharers, and interested sharers – with different memberships. We suggest that local agencies consider broader sharing mechanisms across resource types and time (i.e., before, during, and after evacuations).

Keywords: Joint Choice Modeling, Multi-Choice Latent Class Choice Model, Portfolio Choice Model, Hurricane Evacuations, Sharing Economy

Note: Slight editorial difference may exist between this pre-print and the final published article.

1. INTRODUCTION

In the last two decades, the sharing economy has upended traditional economic structures by offering platforms to share and obtain goods quickly, efficiently, and more cost effectively, especially in the transportation and hospitality industries. This rapid growth has also coincided with multiple disasters in the United States (US). Since Hurricane Sandy in 2012, sharing economy companies – such as Uber, Lyft, and Airbnb – have increased their actions in disaster response and relief (Wong et al., 2018a). Research has also found that private individuals could augment existing resources by offering transportation and sheltering to other evacuees. Recent work has found both supply (Wong and Shaheen, 2019; Wong et al., 2020a) and demand (Li et al., 2018; Borowski and Stathopoulos, 2020) for shared resources in disasters. However, little is known about the factors that influence sharing willingness in disasters. Indeed, Wong and Shaheen (2019) which focused on wildfire evacuees and Wong et al., (2020a) which used the same dataset presented in this study only presented descriptive statistics on willingness to share, concerns related to sharing, and capacity of vehicles/homes. A gap remains on the factors influencing sharing.

At the same time, travel behavior analysis through discrete choice modeling has begun to expand traditional model structures to assess correlated and interdependent choices. While traditional binary and multinomial logit models are parsimonious and easy to interpret, separated models for multiple choices (i.e., one model for each choice) fail to capture potential correlation (if present). Moreover, different types of joint models may yield varying results as the underlying assumptions and model structure are not equivalent. For example, for joint modeling, sequential logit models assume that choices are made in sequence over time (Fu and Wilmot, 2004), but nested logit models make no temporal assumption (Bian, 2017). The development of other types of joint models (such as the portfolio choice model) in the travel behavior field have offered a new opportunity to assess correlations among multiple choices. In our context of evacuations, different types of disaster resources can be provided at different points of time before, during, and after an evacuation, leading to multiple sharing scenarios. Given the potential of the sharing economy and a multi-scenario context, we developed two research questions:

1. What factors influence the willingness to share resources – transportation and/or sheltering – in a hurricane evacuation?
2. How do different model types using the same data uncover different behavioral nuances related to the sharing economy?

This paper explores the willingness of private individuals to share resources across four scenarios in evacuations using an online survey for Hurricane Irma in 2017 (n=645), collected from October to December 2017, and a subset of evacuees from the survey (n=368). We assess the factors that influence sharing willingness through three models. First, we develop four simple binary logit models for each sharing scenario: 1) share transportation before evacuating; 2) share transportation while evacuating; 3) share shelter at a cost; and 4) share shelter for free. However, this model construction fails to consider potential joint preferences or dislikes between sharing scenarios. Consequently, we next develop a portfolio choice model (PCM) that captures dependency among sharing scenarios without hierarchical or sequential assumptions. However, this model does not identify if there exists heterogeneity in the population, who may respond to the four scenarios differently. Thus, we finally develop a multi-choice latent class choice model (LCCM) that estimates multiple scenarios via a latent class choice model (LCCM) structure, segmenting the population into different classes through demographics. As each model attempts to overcome the limitations of the other, we found sometimes similar and other times different factors that impact sharing willingness in evacuations. We show that model construction – such as if the model identifies jointness or heterogeneity – plays an important role in the model results and their interpretation.

2. LITERATURE REVIEW

We first briefly present literature on the shared resource strategy in evacuations, joint modeling methods, and latent class choice models.

2.1 Shared Resource Strategy for Evacuations

The sharing economy is a collection of transactions and mechanisms where goods and services are shared or obtained, typically via the Internet and information communication technologies (Hamari et al., 2016). The sharing economy is often split between business-to-consumer (B2C) and peer-to-peer (P2P) transactions. While the sharing economy extends into diverse marketplaces (e.g., Craigslist, eBay), we focus our study on transportation and sheltering, two key logistic resources in evacuations. Logistic availability of vehicles and shelter (capacity) along with the demand for these resources heavily impact evacuation outcomes (see Lindell et al., 2019 for an overview). The majority of evacuees use private vehicles to evacuate from hurricanes, which ranges from 87% to 96% depending on the study (Prater et al. 2000; Lindell et al. 2011; Wu et al. 2012; Wu et al. 2013; Wilmot and Gudishala 2013; Wong et al. 2018b). Other evacuees receive rides (often from family and friends) or take public transit. For sheltering, the majority of evacuees (between 44% to 70%) stay with friends or family during the evacuation (Prater et al., 2000; Whitehead, 2003; Smith and McCarty, 2009; Cheng et al., 2011; Lindell et al., 2011; Wu et al., 2012; Wilmot and Gudishala, 2013; Wu et al., 2013; Yin et al., 2014; Wong et al., 2018b). These studies found that about 2% to 11% of evacuees use public shelters, while the remaining tend to stay at hotels or motels. Wong et al. (2018b) found that 5% of evacuees sheltered via a P2P sharing economy service (e.g., Airbnb), indicating the growth of this platform for disaster sheltering.

While the current transportation mode and sheltering split helps agencies prepare for future events, these findings mask the demand for resources from vulnerable and underserved populations. For example, two large at-risk cities for hurricanes – Houston and Miami – have carless populations of 8.1%, and 18.6%, respectively (U.S. Census Bureau, 2019). This is equivalent to over 180,000 and over 85,000 people, respectively, in need of transportation during a hurricane. If this demand is not met or resources are not provided, disasters can leave devastating impacts on communities. This was acutely felt after Hurricane Katrina, when the city of New Orleans, Louisiana failed to provide adequate transportation and sheltering assistance (Renne, 2006) to hundreds of thousands who were identified as needing substantial help (Wolshon, 2002). While progress has been made in addressing this equity concern, considerably more resources are needed to ensure that all people, especially those most marginalized are able to evacuate safely. These social equity concerns remain a key area of research in the evacuation field (see Fothergill et al., 1996; Fothergill et al., 1999; Sorensen and Sorensen, 2007; Cahalan and Renne, 2007; Renne et al., 2008; Sanchez and Brenman, 2008; Renne et al. 2009; Rodriguez et al., 2017; Renne and Mayoraga, 2018 for overviews).

To address some of these equity concerns, Wong et al. (2018a) suggested that the sharing economy – whether through businesses (i.e., B2C) or private residents (i.e., P2P) – could be leveraged to supplement public resources and increase equitable evacuation outcomes. Research has found that sharing economy companies, primarily Airbnb, Lyft, and Uber, have been active in at least 30 U.S. disasters since Hurricane Sandy in 2012 (Wong et al., 2020a). The growth of these companies has coincided with a rise of highly structured disaster response and relief mechanisms implemented by these companies across multiple geographies and hazard types. High-ranking experts across multiple sectors recognized that the sharing economy could add adaptable and flexible resources to agencies, while also providing situational awareness and unique communication mechanisms (Wong et al., 2020a). Yet, experts were concerned that the sharing economy might fail to: 1) ensure that resource providers are reliable, safe, and trained for disaster situations; 2) reduce road and communication network congestion; 3) overcome the digital divide (i.e., inequality in accessing computers/Internet); and 4) provide low costs or equitable outcomes (Wong et al., 2020a). Regarding social equity, research has also found that significant barriers remain for multiple underserved groups in using shared resources, both mobility and sheltering, in a disaster (Wong et al., 2020b).

A more recent limitation has been the impact of the COVID-19 pandemic. Research has found that COVID-19 has mostly led to significant drops in ridership for most shared mobility systems, along with new health protocols, changes in services, altered operations, and lower trust of shared services (Menon et al., 2020; Shaheen and Wong, 2021). The COVID-19 pandemic has also increased concerns related to the spread and exposure of the virus during evacuations (Pei et al., 2020). To address this, new research has developed immediate checklists for multiple emergency management topic areas including transportation, evacuations, and sheltering (Wong et al., 2020f) and general guidance for evacuation planning during COVID-19 (Campbell et al., 2021). The implication of the pandemic is that low trust of shared mobility may become the leading limitation of a sharing economy strategy in future evacuations. Indeed, a study on evacuations from floods, ridesharing, and the pandemic by Borowski et al. (2021) found that those with higher health concerns from the pandemic were less willing to share resources.

With this assessment of key benefits and limitations, research has also focused on a P2P model. Li et al. (2018) determined that ride-hailing could be a viable evacuation strategy for a city in China, and carless evacuees would opt to take these transportation options, indicating clear demand. Wong et al. (2020a) and Wong and Shaheen (2019) found that individuals were somewhat willing to offer housing resources to evacuees for a future hurricane and wildfire, respectively. Moreover, the research found that a substantial number of individuals were willing to offer transportation to evacuees before and during the evacuation, and a significant number of evacuating vehicles had spare capacity (88.9% of evacuees with one or more spare seatbelts). Borowski et al. (2021) found similar results: a significant portion of a flood-risk sample were willing to give rides to evacuees (including to those that they did not know). The research developed a random parameter logit model to identify demographic variables and situational variables that impacted willingness (Borowski et al., 2021). Recent work has also found that for no-notice evacuations, there is substantial demand for transportation via transportation network companies or ridesourcing in urban evacuations, and demographic factors (e.g., race, income, gender) and disaster-factors (i.e., severity, evacuation distance, immediacy) impacted demand (Borowski, 2020). Other work has found that social networks can be a strong influencer on evacuation choices (Madireddy et al., 2015; Sadri et al., 2017a; Sadri et al. 2017b; Sadri et al., 2018). The progress of this research remains in its nascent stages, despite the development of policy recommendations for a sharing economy strategy (Wong et al., 2020a; Wong and Shaheen, 2019).

2.2 Joint Modeling Research

Efforts to jointly model multiple choices using methods in discrete choice analysis have been gaining significant momentum in recent years. Early work on nested logit models, which allows for the estimation of dissimilarity parameters between alternatives in defined nests, found that these models could successfully account for correlations of alternatives (see McFadden, 1981; Koppelman and Wen, 1998; Wen and Koppelman, 2001; Hensher and Greene, 2002 for overviews). Nested logit models have also been developed to evaluate multiple choices, such as home, workplace, and commute mode (Abraham and Hunt, 1997), accessibility to transportation modes (Polydoropoulou and Ben-Akiva, 2001), and residential mobility and housing location choice (Lee and Waddell, 2010) to name a few. Various approaches have also been explored to model multiple choices in both economics and transportation, such as cross nested logit model (Vega and Reynolds-Feighan, 2009; Hess et al., 2012; Yang et al., 2013), structural equations modelling (see Golob, 2003 for full review; see Van Acker and Witlox, 2010 and Ding et al., 2018 for examples), simultaneous logit models (Ouyang et al., 2002; Ye et al., 2007), and simultaneous bivariate probit models (Ye et al., 2007). A significant amount of literature has also developed discrete-continuous models (and its variations) to jointly model continuous variables in a discrete choice context (see examples in Bhat, 2005; Bhat, 2008 Fang, 2008; Vance and Hedel, 2007).

More recently, Eluru et al. (2010) employed a joint Generalized Extreme Value (GEV)-based logit regression model for combined residential location choice, vehicle count by type choice, and vehicle usage using a copula-based framework. This framework was able to accommodate a significant number of choice dimensions through repeated discrete-continuous choice occasions. Results indicate significant dependency among the choice dimensions, despite the significant analytical and computational burdens of such a complex model. Paleti et al. (2013) built a multi-dimensional model with six different travel activity choice dimensions (i.e., residential location choice, work location choice, commuting distance, vehicle ownership, commute mode choice, and number of stops made on commute tours) and estimated choices jointly using a Maximum Approximated Composite Marginal Likelihood (MACML) approach. The results show that the choice dimensions are interrelated, both through direct observed structural relationships and through correlations across unobserved factors affecting multiple choice dimensions. For example, residential location choice impacted work location choice, while both residential and work location choices together are correlated with commuting distances. Similarly, Tran et al. (2016) developed a joint model of residential location, job location and commuting mode choice using data collected in Hanoi, Vietnam and confirmed significant interdependencies between these choice dimensions. Tran et al. (2016) followed the methodology in Paleti et al. (2013) by estimating random parameters that captured interdependencies in the utility equations for each choice. Guo et al. (2020) jointly modelled long-term residence choice, job choice decision, and short-term commute mode choice using panel data collected from Shenyang, China. The resulting model, a multi-dimensional mixed logit model, found significant dependencies among choice. Finally, recent work in tourism choice has developed portfolio choice models (PCMs), which reframed the choice set as a bundle of choices (for example Van Cranenburgh et al., 2014a). The work, using the efficient and easily-interpretable PCM framework, found strong joint preference between duration of vacation and transportation mode.

2.3 Latent Class Choice Models (LCCMs)

Accounting for taste heterogeneity in the population is essential for demand forecasting and estimating unbiased models. This is especially true for the evacuation and sharing economy purpose since peoples' preferences generally vary by their household structure, sharing attitudes, and individual characteristics. Incorporating this heterogeneity into modeling offers clearer policy-relevant recommendations for a shared resource strategy. Currently, two popular approaches in the assessment of travel behavior have been used for representing heterogeneity (i.e., variations in tastes) across individuals: 1) mixed multinomial logit model (MMNL) and 2) latent class choice model (LCCM). The MMNL model extends traditional multinomial logit model by allowing for random coefficients (typically distributed normally) on observed attributes that capture heterogeneity. In the special case that the coefficient distribution in MMNL is not continuous (i.e., discrete), we obtain the latent class choice model (Walker, 2001; Greene and Hensher, 2013). In LCCM, we stratify people into different classes, and unobserved heterogeneity is captured through the class membership model. Within each class, individuals behave similarly with homogeneous preferences (i.e., identical coefficients for attributes of the decision-maker). Many studies using different datasets have shown that the LCCM can represent heterogeneity across population segments, which results in improved prediction accuracy and interpretation power over the multinomial logit model and mixed logit model (Greene and Hensher, 2003; Shen, 2009; Vij et el., 2013). The LCCM approach has been widely applied across the transportation field in areas including: transportation mode choice (Atasoy et al., 2011; Vij et el., 2013; Molin et el., 2016;); residential location (Walker and Li, 2007; Carrel et al., 2011; Liao et al., 2015); innovative mobility disruption (El Zarwi et al., 2017); pricing (Hensher and Greene, 2010; Hetrakul and Cirillo, 2014); aviation (Wen and Lai, 2010); electric vehicle interest (Ferguson et al., 2018); building evacuations (Haghani and Sarvi, 2016), and disaster choice-making (Urata and Pel, 2018; McCaffrey et al., 2018; Wong et al., 2020c).

2.4 Advances in Choice Modeling in Evacuations

In the past few decades, discrete choice models have been widely used to understand evacuee choice-making. Most recent hurricane studies have concentrated on one dimension of behavior, in particular whether to evacuate, through traditional binary logit models (Whitehead et al., 2000; Zhang et al., 2004; Smith and McCarty, 2009; Stein et al., 2010; Hasan et al., 2012; Huang et al., 2012; Murray-Tuite et al., 2012; Murray-Tuite and Wolshon, 2013; Wong et al., 2018b) and mixed logit models (Deka and Carnegie, 2010; Solís et al., 2010; Hasan et al., 2011; Xu et al., 2016; Yin et al., 2016). A number of other choices in evacuations have been assessed in isolation, including: mode choice (Deka and Carnegie, 2010; Sadri et al., 2014a); shelter and accommodation type (Whitehead et al., 2000; Mesa-Arango et al., 2013); route choice (Sadri et al., 2014b; Sadri et al., 2015); and reentry (Siebeneck et al., 2013). A review of this hurricane literature using discrete choice models can be found in Wong et al., (2018b). A sizable literature also exists for evacuee behavior in other hazards, such as wildfires (see Lovreglio et al., 2019; Kuligowski, 2020; Wong et al., 2020d for reviews).

Despite this considerable work using traditional choice models, advances along several fronts have offered more nuanced and in-depth assessments of evacuation choice-making, especially within a joint context. First, models related to departure time have considered the sequential nature of choice-making, in particular how the decision to evacuate or stay must be made before a departure time is chosen (Fu and Wilmot, 2004; Gudishala and Wilmot, 2012). Sarwar et al. (2018) extended this work through a joint model that also captured heterogeneity through random parameters.

Second, discrete-continuous joint modeling has extended the sequential approach, providing stronger evidence for the need to consider choices jointly. Using a discrete-continuous modeling framework, Gehlot et al. (2019) combined a continuous hazard duration model and an ordered probit model that accounted for (and found) correlation between hurricane evacuation departure times and travel times. For no-notice emergency events, Golshani et al. (2019) used a similar approach when combining evacuation destination and departure time into a joint model including a multinomial logit model and an accelerated hazard duration approach. Third, nesting structures have been employed to assess the joint relationship of multiple types of choices in evacuations. To test correlation between evacuation destination and accommodation type, Damera et al. (2020) estimated a nested logit, determining that the nested structure significantly affected the empirical results. Bian (2017) and Bian et al. (2019) leveraged nested logit models and found linkages between hurricane evacuation mode and destination type. The latter of these studies also used multiple data sources, adding validity to the need to model decisions jointly. Finally, work has been conducted to consider multiple choice (beyond two) within a single modeling structure. Wong et al. (2020c) and Wong et al. (2021a) developed a portfolio choice model (PCM) for hurricanes and wildfires, respectively, combined multiple evacuation choices (i.e., departure time, mode, route, shelter, destination) into a single model, and found significant correlation among the choices. Altogether, these choice modeling advances in evacuations all point away from considering choices in isolation. Choices, in many contexts, are correlated and interdependent and should be modelled concurrently (i.e., jointly).

In another advance, evacuation behavior research has begun to employ LCCMs, capturing heterogeneity of individuals impacted by disasters and membership of people to different groups based on choice-making and demographics. In a study of tsunami evacuation choice, Urata and Pel (2018) leveraged an LCCM that incorporates risk recognition, risk education, and demographic variables to help identify different classes of people that make different evacuation choices. A similar analysis was conducted using risk and demographic variables for a wildfire evacuation, finding a clear choice and membership distinctions between an "evacuation class" and a "defend class" (McCaffrey et al., 2018). Also in a wildfire, Wong et al. (2021a) found similar results to McCaffrey using an LCCM for the decision to evacuate or stay, finding an "evacuation keen class" and an "evacuation reluctant class." Finally, for hurricane evacuations, Wong et al. (2020c) determined the same "keen" and "reluctant" classes that were impacted differently by mandatory evacuation orders.

With advances in evacuation modeling that show that evacuation choices could be modelled jointly, we recognize that other choice contexts, including multiple stated preference scenarios, could also be modelled jointly. Two pathways emerge for understanding how people might consider sharing resources in an evacuation. First, the PCM model offers two key benefits over most other joint models: they can be estimated as a multinomial logit, and they do not require any hierarchical or sequential assumptions. Despite, these benefits, one key limitation is that it fails to account for unobserved heterogeneity based on lifestyle preferences and other characteristics. Indeed, unobservable (latent) classes of individuals are unlikely to behave the same, especially when considering concurrent multiple choices. Second, with this limitation in joint modeling in mind, we employ a multi-choice LCCM, which can capture conditional independence of choices and find unobserved classes that behave differently. In our context of a shared resource strategy, we consider the sharing scenarios simultaneously in the same framework, as to identify the probability that a class of individuals (with similar characteristics) would choose to share resources across *all* scenarios. This “multi-choice” extension of the traditional LCCM can handle multiple scenarios and identify individuals’ potential segments and heterogeneous preferences for offering transportation and sheltering resources in an evacuation.

3. METHODOLOGY

3.1 Hurricane Irma Survey Data

Hurricane Irma, in September 2017, was one of the strongest Atlantic hurricanes in history. Forecasters were also unsure of the precise landfall location of Irma in Florida, leading to a mass evacuation of over six million people (Maul, 2018). The storm caused approximately $50 billion in damages and led to 92 deaths in the U.S. (NOAA, 2018). From October to December 2017, we distributed an online survey to Florida residents impacted by Hurricane Irma.

Considering the wide-spread evacuations and potential for displaced evacuees, we posted the online survey to various locations including Facebook, Twitter, online websites, and alert subscription services with assistance from emergency management, transportation, transit, and planning agencies in several targeted counties. These agencies were selected based on jurisdiction population and disaster proximity. Respondents were incentivized with the opportunity to win one of five $200 gift cards. The Hurricane Irma survey yielded 1,216 responses, 938 completed surveys (74% completion rate), and 645 final responses after intensive data cleaning for modeling. For cleaning, respondents who were removed from the final responses included those who did not answer: 1) if they evacuated or stayed during Hurricane Irma; 2) their willingness to share resources in a disaster; and 3) key demographic characteristics (e.g., gender, age, education, county of residence). Respondents who “completed” the survey but did not answer questions were also removed. The demographic characteristics are provided in Table 1 for the full dataset, which includes the subset of 368 evacuees. We also present key choices of subset of 368 evacuees in Table 2.

Table 1: Demographic Characteristics of Hurricane Irma Survey Respondents (n=645)

Individual Characteristics			
Gender		**Primary Transportation Mode**	
Female	81.9%	Drive alone using automobile	94.3%
Male	18.1%	Work from home	1.7%
		Carpool/vanpool	0.9%
Age		Bus	0.8%
18-24	3.1%	Bicycle	0.6%
25-34	26.0%	Walk	0.3%
35-44	28.7%	Motorcycle/scooter	0.3%
45-54	21.7%	Shared mobility	0.2%
55-65	14.9%	Other	0.9%
65+	5.6%		
		Mobile Phone Type	
Race		Own a smartphone	96.3%
White	94.0%	Own a non-smartphone	3.4%
Black or African-American	1.6%	Do not own a cell phone	0.3%
Mixed	1.1%		

Asian	0.9%	**Mobile Phone Plan**	
Native American/Alaska Native	0.2%	Call, text, and internet with data	95.7%
Pacific Islander	0.2%	Only call and text available	4.2%
No answer/Prefer no answer	2.2%	Do not own a cell phone	0.2%
Ethnicity		**Used Ridesourcing Before**	
Not Hispanic	89.5%	Yes	49.0%
Hispanic	6.7%	No	51.0%
No answer/Prefer no answer	3.9%		
		Used Carsharing Before	
Education		Yes	13.6%
High school graduate	6.5%	No	86.4%
Some college	18.6%		
2 year degree	12.9%	**Used Homesharing Before**	
4 year degree	32.1%	Yes	37.8%
Professional degree	26.4%	No	62.2%
Doctorate	3.6%		
		Previous Hurricanes Experienced	
Employment		0	3.6%
Employed full time	65.7%	1 or 2	31.3%
Employed part time	10.2%	3 or 4	17.5%
Unemployed	9.6%	5 or more	47.6%
Retired	8.7%		
Disabled	2.3%	**Previous Evacuations Experienced**	
Student	2.2%	0	46.4%
No answer/Prefer no answer	1.2%	1 or 2	39.4%
		3 or 4	8.8%
		5 or more	5.4%

Decision Making Role	
I am the sole decision maker	18.6%
I am the primary decision maker with input from another household member	22.3%
I share equally in making decisions with another household member(s)	56.4%
I provide input into the decisions, but I am not the primary decision maker	2.0%
Another person is the sole decision maker	0.6%

Household Characteristics

County of Residence		**Household Size**	
Brevard	53.2%	1	10.7%
Lee	17.2%	2	36.6%
Collier	13.3%	3	18.4%
Miami-Dade	3.7%	4	17.8%
Monroe	2.6%	5	12.1%
Pinellas	2.9%	More than 5	4.3%
Broward	2.5%		
All other counties	4.5%	**Household Characteristics**	
		Household with Individual(s) with a Disability	16.4%
Residence by Florida Region		Household with Child(ren)	44.8%
Northeast/Central-East	54.7%	Household with Older Adult(s) (65+)	15.0%
Southwest	32.6%	Households with Pet(s)	77.1%
Southeast	9.8%		
Central-West*	2.9%	**Household Income**	

Residence Structure	
Site build (single home)	76.6%
Site build (apartment)	19.1%
Mobile/manufactured home	4.3%
Homeownership	
Yes	69.3%
No	30.7%
Live in FEMA* Flood Risk Area	
Yes	39.5%
No	47.9%
I don't know	12.6%
*Federal Emergency Management Agency	
Length of Current Residence	
Less than 6 months	9.5%
6 to 11 months	7.9%
1 to 2 years	22.6%
3 to 4 years	18.6%
5 to 6 years	9.8%
7 to 8 years	6.4%
9 to 10 years	4.0%
More than 10 years	21.2%
Displacement after Storm	
Same Residence	96.0%
Displaced	2.0%
No answer	2.0%
Less than $20,000	4.7%
$20,000 - $49,999	19.8%
$50,000 - $69,999	13.9%
$70,000 - $99,999	19.7%
$100,000 - $149,999	17.7%
More than $150,000	12.4%
No answer/Prefer no answer	11.8%
Access to Internet at Home	
Yes	98.3%
No	1.7%
Number of Vehicles in Household	
0	0.5%
1	24.7%
2	52.4%
3	16.0%
4	3.7%
5	2.2%
More than 5	0.6%
In-Vehicle or Smartphone Navigation	
Yes	87.9%
No	12.1%
Number of Spare Beds/Mattresses	
0	16.0%
1	25.1%
2	28.4%
3	16.9%
4	7.8%
5	2.6%
More than 5	3.3%

Table 2: Key Choices of Hurricane Irma Evacuees (n=368)

Evacuated from Irma	
Yes	57.1%
No	42.9%
Received a Mandatory Evacuation Order	
Yes	46.2%
No	53.8%
Departure Date	
Before Tuesday, Sept. 5	1.6%
Tuesday, Sept. 5	2.7%
Wednesday, Sept. 6	15.8%
Thursday, Sept. 7	22.3%
Friday, Sept. 8	32.3%
Multiple Destinations	
Yes	28.0%
No	72.0%
Mode Choice	
One personal vehicle	65.8%
Two personal vehicles	21.5%
Aircraft	4.1%
More than two personal vehicles	2.7%
Non-household carpool	2.2%
Recreational vehicle (RV)	1.6%
Rental car	1.6%
Bus	0.5%

Saturday, Sept. 9	22.6%
Sunday, Sept. 10	0.8%
Monday, Sept. 11 and Later	1.9%
Departure Timing by Hour	
12:00AM-5:00AM	16.0%
6:00AM-11:00AM	32.9%
12:00PM-5:00PM	34.2%
6:00PM-11:00PM	16.8%
Destination by State	
Florida	51.4%
Georgia	12.0%
Tennessee	6.8%
North Carolina	5.7%
Alabama	4.9%
South Carolina	3.5%
Virginia	2.4%
Louisiana	1.6%
Mississippi	1.6%
Ohio	1.6%
Pennsylvania	1.6%
All other states (under 5 respondents)	6.8%
Within County Evacuation	
Yes	17.1%
No	82.9%
Shelter Type	
A friend's residence	15.8%
A family member's residence	43.5%
A hotel or motel	27.4%
A public shelter	3.5%
Peer-to-peer service (e.g., Airbnb)	4.3%
A second residence	2.7%
A portable vehicle (e.g., camper, RV)	2.2%
Other	0.5%
Towed Large Item During Evacuation	
Yes	4.9%
No	95.1%
Spare Seatbelts Across All Evacuating Vehicles	
0	11.1%
1	8.4%
2	13.9%
3	17.4%
4	12.8%
5	13.0%
More than 5	19.8%
Didn't Use Personal Vehicle	3.5%
Primary Route by Road Type	
Highways	64.1%
Major Roads	13.6%
Local Roads	4.1%
Rural Roads	1.4%
No Majority Type	16.8%
Usage of GPS for Routing	
Yes, and followed route	63.6%
Yes, but rarely followed route	6.5%
No	29.9%
Reentry Date	
*Before Sunday, Sept. 10	10.9%
Sunday, Sept. 10	1.6%
Monday, Sept. 11	18.5%
Tuesday, Sept. 12	22.0%
Wednesday, Sept. 13	12.5%
Thursday, Sept. 14	8.2%
Friday, Sept. 15	5.4%
Saturday, Sept. 16	4.1%
Sunday, Sept. 17	7.1%
After Sunday, Sept. 17	9.8%

*Respondents may have confused "reentry" with the evacuation date or decided to return home before landfall if their residence was no longer at risk due to a change in the hurricane path.

The dataset has several key limitations that limits some conclusions. First, the online survey exhibits self-selection bias as individuals opt into the study. We attempted to address this by providing a lottery incentive and asking over 10 agencies with different functions (e.g., transportation, emergency management) and news sources to distribute the survey. Second, we acknowledge online surveys have sampling bias as they only reach individuals with Internet access, often oversampling wealthier populations. Third, we also found that respondents were concentrated in three counties – Brevard, Lee, and Collier. The sample geographies are wealthier, more highly educated, and racially whiter than the impacted area and Florida. While we worked with several agencies in larger counties (e.g., Miami-Dade, Broward, Pinellas, Hillsborough), we found response rates to be lower, possibly due to the lower impact of Hurricane Irma in those areas and the more restrained survey distribution by agencies.

We were also unable to determine if those not represented in the survey (e.g., vulnerable populations) were willing to share resources. Future work will be needed in post-disaster online surveying to obtain a more representative population, while still ensuring that the survey is low-cost and rapid. Fourth, we did not ask in the survey *who* someone would be willing to share with, limiting our results to an unidentified person. The receiver of shared resources likely impacts the willingness of the sharer to provide their resources. Fifth, we note that some of the demographic questions did not receive an answer or received a prefer not to answer. These small percentages are unlikely to affect the final modelling results, though small levels of bias may be introduced due to these non-answers. Most tested variables had 100% response rates. Finally, since surveys were distributed by public agencies, there is a possibility that some survey respondents were public officials and not private individual. Public officials with roles in the disaster may be inhibited from providing *their own* resources in a disaster due to their primary job. Future surveys should include a question regarding employment with a public agency involved in disasters to overcome this limitation.

Despite these limitations, the dataset remains fairly robust, particularly in its ability to capture a wide number of questions for a reasonable sample size for post-disaster surveys. The sample was also moderately diverse in representation and generally mirrored the demographics of our targeted distribution areas in Florida. Moreover, a telephone survey (Mason-Dixon Research and Polling, 2017) found a compliance rate of 57%, which is similar to the compliance rate of 70% in our survey. Using traffic data, Feng and Lin (2020) found a variety of compliance rates for Miami (~30%), Tampa (~30%), and Key West (~80%). Since our sample includes respondents across Florida, in aggregate our data appears reasonable. Focusing only on Southwest Florida, we found a compliance rate of 83% in our data, which mirrors rates in Key West from Feng and Lin (2021). Additional work using mobile phone data may further determine if our data was robust. Given the limitations of this work, any interpretation of results should keep in mind that the sample likely represents a captive audience with a greater understanding of disasters, needs of others in hazards, and emergency procedures. This may reduce the reliability of the model results, but not likely enough to shift the interpretation of results due to heterogeneity in the sample and variety of tested variables. We also note that the sample that evacuated and the sample that did not evacuate are relatively similar across key variables. The two samples do diverge on a few demographic characteristics. For example, more evacuated respondents live in Southwest Florida while more non-evacuated respondents live in Northeast/Central East Florida. Non-evacuated individuals have slightly higher homeownership rates and live somewhat more often in single family homes. Finally, more evacuated respondents said that they live in a Federal Emergency Management Agency (FEMA) risk zone (i.e., areas at risk of a 100-year flood defined by FEMA [identified on the Flood Insurance Rate Map]). Given the similarity of all other key variables between the evacuated sample and the non-evacuated sample, we determine that sample differences have minimal effect on the model results and interpretation.

3.2 Hurricane Irma Sharing Scenarios

We developed four sharing scenarios where individuals were asked about their willingness to provide resources to a non-household member in a future disaster on a Likert scale from extremely unlikely (1) to extremely likely (5) (see Table 3). For modeling, we wanted to assess more clearly *actual* behavior, as opposed to *intended* behavior. Consequently, we split responses into two categories:

1) Extremely likely to share; and

2) All other answers.

This binary demarcation was intended to define a group of individuals who would actually share in a disaster. Given the concerns related to sharing (as noted in Wong et al., 2020a), we generally wanted to conservatively identify a group of individuals with the most propensity to share. Those who stated they would be extremely likely to share would have a higher probability to share, regardless of the context of the situation. Moreover, this division allowed for a simpler model structure when estimating our models, especially given the lower sample sizes. We also note that since we only asked evacuees about their willingness to offer transportation resources, our joint models (and the two transportation binary logit models) have only a sample size of 368. This limitation in the survey design – to only show evacuees the question related to willingness to share transportation – requires fixing in future iterations of post-disaster surveys. We note additional limitations of the scenario design throughout the following model results section.

Using these four scenarios (split into two categorical responses), we developed four binary logit models that identified the factors that increase or decrease sharing willingness. These models are independent from each other and isolate each sharing scenario. We present the models in the same table to highlight some similarities and differences in the variables that influence sharing.

Table 3: Description of Sharing Scenarios for a Future Disaster

Scenario	**1**	**2**	**3**	**4**
Resource Type	Transportation	Transportation	Sheltering	Sheltering
Shorthand Label	S1-Transport-Before	S2-Transport-During	S3-Shelter-Cost	S4-Shelter-Free
Explanation of Scenario	Individual's willingness to offer a ride to other evacuees **before the evacuation process begins**	Individual's willingness to offer a ride to other evacuees **during the evacuation**, enroute to the destination	Individual's willingness to offer shelter to other evacuees at a **cost per night**	Individual's willingness to offer shelter to other evacuees **for free**
Additional Information to Survey Taker	No additional information		Shared home is safe and has not been ordered to evacuate	
Recipient Description	The individual(s) receiving assistance is not specified beyond "individual(s)"			
Question Design	Likert scale from 5 (extremely likely) to 1 (extremely unlikely)			

Likelihood to Share in a Future Disaster of Hurricane Evacuees Only (n=368)				
Extremely likely	29.1%	23.6%	6.5%	20.1%
Somewhat likely	25.3%	24.2%	18.8%	20.7%
Neither likely nor unlikely	10.1%	10.1%	12.8%	13.0%
Somewhat unlikely	16.8%	18.5%	26.6%	13.3%
Extremely unlikely	16.0%	20.9%	35.3%	32.9%
No personal vehicle	2.7%	2.7%		

3.3 Portfolio Choice Model (PCM)

While binary logit models are helpful in isolating effects in one sharing scenario, they do not consider how the scenarios might be correlated. For example, a person who shares in one scenario may be also likely to share in another scenario. To overcome this limitation in the binary logit model construction, we next developed a portfolio choice model (PCM), which captures interdependency among choices via a bundling approach. Choices were combined to form a bundle of choices, which become the new alternatives in the choice set (Dellaert et al., 1997; Grigolon et al., 2012; Van Cranenburgh et al., 2014a; Van Cranenburgh et al., 2014b; Wong et al. 2020c). We combined the four scenarios (each composed of a binary decision) into bundles of choices to reach 16 possible portfolios (2*2*2*2). We assumed independent identically distributed (i.i.d.) EV Type I errors, which led to closed form logit probabilities. Through a PCM structure, we estimated the parameters of the different dimensions, possible interactions, and the impact of demographic characteristics on the dimensions. For the PCM, we retained all secondary interactions to provide a clear comparison of joint preferences. We also retained statistically significant demographic variables along with several insignificant variables that were policy relevant and/or significant in the binary logit models. In this sense, we opted to produce a less efficient model with more variables but less bias. While the sample size of 368 was relatively small, this sample was sufficient for the construction of PCMs – since the model follows the methodology of a multinomial logit function (see Dellaert et al., 1997 for more background on the PCM). We estimated the PCM via the Python package Pylogit (Brathwaite and Walker, 2018).

3.4 Methodology of the Multi-Choice LCCM

While the PCM identifies jointness in sharing scenarios, the model does not identify heterogeneity in the population. To better account for unobserved preferences and classes of individuals (while still assessing jointness in scenarios), we developed a multi-choice LCCM that connects scenarios (i.e., choices) via a membership structure. Following the methodology in El Zarwi et al. (2017), we found the probability an individual n makes a choice y for alternative i (where $i = 1$ is extremely likely to share and $i = 0$ is not extremely likely to share), which was conditional on decision-maker characteristics (Z_n), alternative specific characteristics (X_{ni}), and membership to latent class s (where q_{ns} equals one and zero otherwise), expressed as follows:

$$P(y_{ni}|Z_n, X_{ni}, q_{ns}) \forall i \in \{0,1|y_{ni}\} \quad (1)$$

Assuming the decision-maker maximizes their utility (i.e., random utility maximization [RUM] models), we formulated that the utility of sharing or not associated with individual n conditional on the individual belonging to latent class s as:

$$U_{ni|s} = V_{ni|s} + \varepsilon_{ni|s} = x_n' \beta_s + \varepsilon_{ni|s} \quad (2)$$

where $V_{ni|s}$ was the systematic utility, x_n' was a vector of decision-maker characteristics and alternative attributes, β_s was a vector of estimable parameters specific to latent class s, and $\varepsilon_{ni|s}$ were disturbances associated to the utility. We assumed i.i.d. EV Type I errors across all individuals, alternatives, and latent classes. We expressed the probability from Equation 1 in terms of the utility from each latent class into the classical RUM function, where C was the choice set, as follows:

$$P(y_{ni}|Z_n, X_{ni}, q_{ns}) = P\left(U_{ni|s} \geq U_{ni'|s} \forall i' \in C\right) = \frac{\exp\left(V_{ni|s}\right)}{\sum_{i'=1}^{|C|} \exp\left(V_{ni'|s}\right)} \quad (3)$$

For the above formulation, we only considered a single choice (y_{ni}). We expanded this formulation to consider the role of multiple choices connected via the latent classes. We considered the four sharing scenarios (Table 3) as separate choices, denoted as choice context M:

For choice context 1 to M:

$$P^1(y_{ni}^1|Z_n, X_{ni}, q_{ns}) = P^1\left(U_{ni|s}^1 \geq U_{ni'|s}^1 \forall i' \in C_m\right) = \frac{\exp\left(V_{ni|s}^1\right)}{\sum_{i'=1}^{|C_1|} \exp\left(V_{ni'|s}^1\right)} \quad (4)$$

$$P^M(y_{ni}^M|Z_n, X_{ni}, q_{ns}) = P^M\left(U_{ni|s}^M \geq U_{ni'|s}^M \forall i' \in C_m\right) = \frac{\exp\left(V_{ni|s}^M\right)}{\sum_{i'=1}^{|C_M|} \exp\left(V_{ni'|s}^M\right)} \quad (5)$$

To estimate the membership model, we found the probability that an individual belongs to a class as denoted by $P(q_{ns}|Z_n)$ where $Z_n$was composed of the decision-maker characteristics. The utility derived from latent class s was:

$$U_{ns} = V_{ns} + \varepsilon_{ns} = z_n' \tau_s + \varepsilon_{ns} \quad (6)$$

where V_{ns} was the systematic utility, z_n' was a vector of decision-maker characteristics, and τ_s was a vector of estimable parameters. Assuming the same error distribution, we expressed the probabilities as:

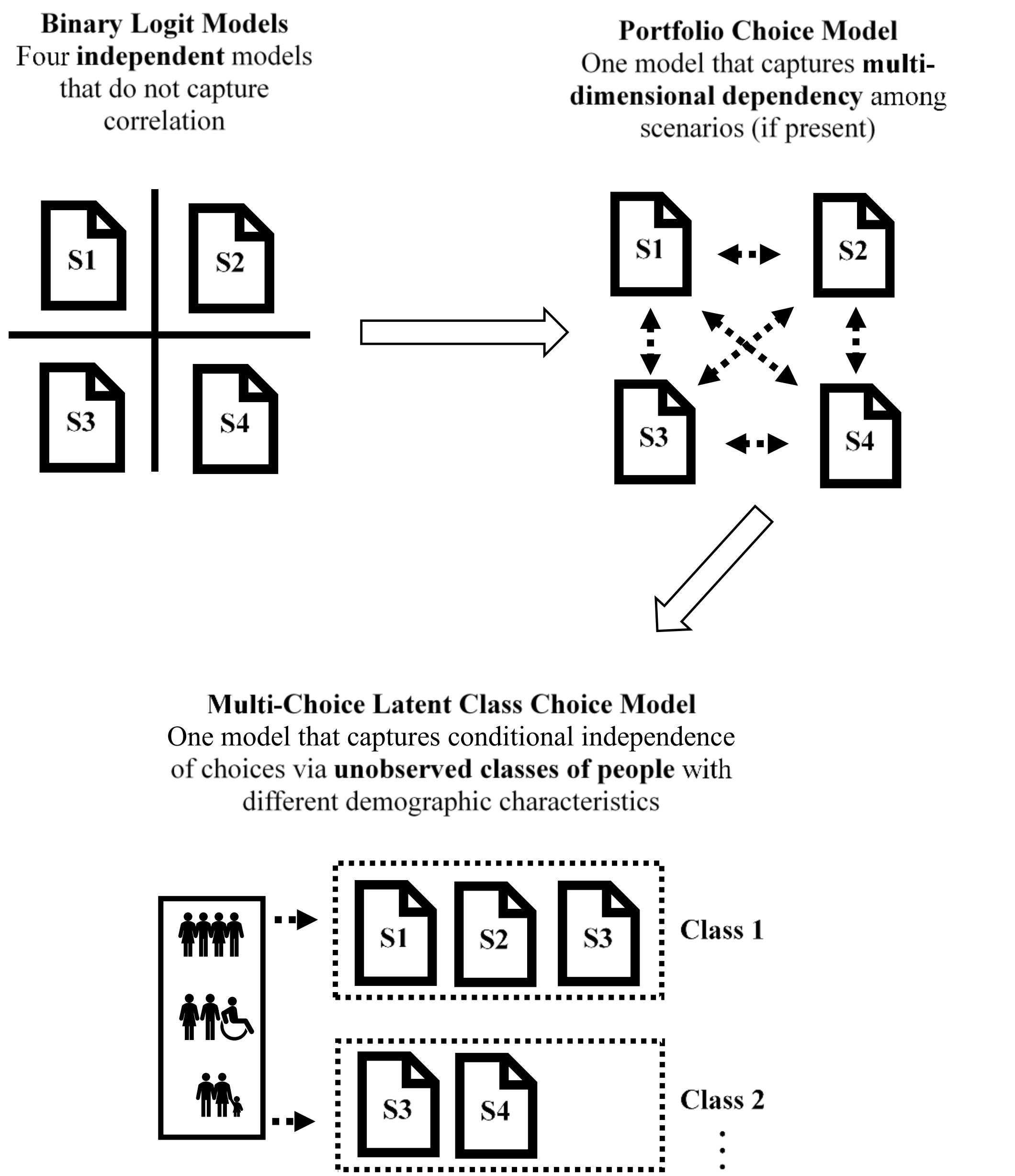
$$P(q_{ns}|Z_n) = P(U_{ns} \geq U_{ns'} \forall s' = 1,2, \dots, S) = \frac{\exp(V_{ns})}{\sum_{s'=1}^{S} \exp(V_{ns'})} \quad (7)$$

Equations 3 and 7 were combined to find the marginal probability, the probability of the choices y^m, across individuals, latent classes, and alternatives to be:

$$P(y^m) = \prod_{n=1}^{N} \sum_{s=1}^{S} P(y_n^M|q_{ns}) P(q_{ns}|Z_n) = \prod_{n=1}^{N} \sum_{s=1}^{S} \left[P(q_{ns}|Z_n) \prod_{m=1}^{M} \prod_{i \in C_m} P\left(y_{ni}^m|Z_n, X_{ni}, q_{n,s}\right)^{y_{ni}^m} \right] \quad (8)$$

To solve this marginal probability equation, we used an expectation-maximization (EM) algorithm, described in depth in El Zarwi et al. (2017). Similar to the PCM, the sample size (n=368) was fairly small. However, given that the construction was similar to a typical LCCM, which requires a similar sample size as both mixed logit and binary logit models, our sample was sufficient for modeling (see Walker, 2001 for more information about LCCMs). However, future research directions should include larger sample sizes in post-disaster surveys for these model types. A graphical overview of the flow of different model types (i.e., binary logit, PCM, multi-choice LCCM) can be found in Figure 1.

Figure 1: Graphical overview and flow of different model types



Notes: Dashed arrows indicate estimation; dashed boxes indicate unobserved classes; undashed boxes indicate observed demographics; scenarios (i.e., choices) are known via the survey

3.5 Methodological Notes

To maintain consistency, we employed a procedure for model development. First, we generally tested the same set of possible independent variables for each of the model types. There were a few exceptions, including: 1) homesharing and spare bed variables for sheltering sharing only; 2) ridesourcing and spare seatbelt variables for transportation sharing only; and 3) evacuation experience from Hurricane Irma for models that included only evacuees (non-evacuees did not make evacuation choices). Second, we built a correlation table of considered variables to reduce multicollinearity effects. We checked each model to ensure that included variables did not have a Person correlation coefficient above 0.4 or below -0.4. Third, we focused on variables relevant to policy and *a priori* expectations. For variable selection, we retained variables with a p-value of 0.25 or lower. This benchmark (rather than a p-value of 0.05, or significance) was chosen to: 1) decrease bias in the final model; 2) enable easy cross-comparison of models; and 3) identify variables that should be considered in future modelling work on the sharing economy in evacuations. In the case of the multi-choice LCCM, membership variables must be estimated across all classes. A variable with a p-value 0.25 or lower for at least one class membership was retained. We acknowledge that our choice of this p-value decreases precision and prevents conclusive results for these variables.

4. RESULTS

We present three sets of models – 1) four binary logit models; 2) a PCM; and 3) a multi-choice LCCM – to analyze the willingness of individuals to share their private resources.

4.1 Binary Logit Model Results

We first present model results and discussion of four independently constructed binary logit models (Table 4). For sharing transportation before evacuating, we found that individuals residing in Southwest Florida were more likely to share. Southwest Florida, which includes the Florida Keys and areas around Fort Myers, was most directly impacted by Hurricane Irma. This recent strike may have served as an instigating event for residents to consider sharing transportation in a future disaster, particularly given the limited evacuation routes in the area (particularly only US Highway 1 for the Florida Keys). These areas may also have stronger social capital than other places in Florida, which has been found to increase sharing in a wildfire case (Wong et al. 2020e). We found that households with children and households living in the same residence for more than ten years were much less likely to share transportation before evacuating. Households with children may have more items to pack (and thus less room for another passenger) and/or may be primarily concerned with their children's safety. This level of concern for safety was displayed through additional trip-making in child-gathering models for a no-notice evacuation developed in Liu and Murray-Tuite (2013). Other research has found that mothers prioritize the safety and security of their children in evacuation decision-making (Brodar et al., 2020). It is not immediately clear why long-term residents would be less likely to share transportation. While research has found that experience and length of residence do not improve preparedness levels (e.g., Chen et al., 2012), long-time residents may be conducting more time-consuming preparedness activities (e.g., boarding up a home) that prevent them from sharing before an evacuation.

For transportation during the evacuation, we found that young adults and those who have experienced three of more hurricanes were less likely to share transportation. Young adults may not have vehicles to share (as found by Klein and Smart (2017) that millennials tend to own less vehicles than previous cohorts if they are economically dependent on their parents) or may lack overall evacuation experience, making them unknowledgeable of the needs of carless individuals. However, those with extensive experience may prioritize different actions over others (e.g., saving possessions over having extra space) that could reduce sharing willingness. We also found that those who evacuated within their county of residence were more likely to share transportation during the evacuation. Those traveling shorter distances may be more willing to make small deviations from their route and help someone for a relatively short amount of time, especially given that over half of the evacuees in this dataset spent ten or more hours evacuating (Wong et al., 2018b).

We found that previous evacuees and homesharing users were more likely to share shelter at a cost. Previous evacuees may have struggled to find housing themselves and would be willing to provide accommodations (or high-quality shelters). Research has found that those who experienced a hurricane were less likely to go to a public shelter than those who did not experience a hurricane, perhaps due to poor shelter quality (Rincon et al., 2001). Those with experience with homesharing (e.g., Airbnb, VRBO) have knowledge of the sharing economy. We also found that white individuals, households with children, and high-income households (above $100,000 per year) were less likely to share. Race may play a role in the perception of trust, a similar result to that of the discrimination of minorities in the sharing economy (see Ge et al., 2016 and Edelman et al., 2017 for evidence of discrimination). Households with children may be concerned about their children's safety, while also preferring to care primarily for children over potential strangers. High-income households likely do not need additional money by charging for accommodations.

Homesharing users were significantly more likely to share shelter for free, probably because of their sharing economy experience (e.g., Airbnb, VRBO). Indeed, Airbnb recently launched a new initiative, Airbnb.org, which extends its Open Homes initiative that encouraged hosts to provide their spaces for free to evacuees (Airbnb.org, 2021). White individuals were less likely to share, which may be again tied to discrimination against evacuees in need of housing (see research by Edelman and Luca, 2014; Edelman et al., 2017 for discrimination in the sharing economy). All other variables were insignificant, indicating that other factors not tested in this model are likely influencing willingness to share.

Overall, we found relatively low model fit (with the exception of sharing shelter for a cost) across the binary logit models. The fit for the model for sharing for a cost is likely influenced by the strong negative constant value and low percentage of respondents who were extremely likely to share in this scenario. We also note that one key limitation of this binary logit analysis is that the models were developed separately. We would intuitively expect that people willing to share transportation before the evacuation would likely share transportation during the evacuation. This intuition is mostly due to the construction of the scenarios (which are relatively similar), but also possible groupings of people as sharers or non-sharers.

Table 4: Estimation of Four Separate Binary Logit Models

Choice 1: Extremely Likely to Share in a Future Disaster
Choice 2: Somewhat Likely, Neither Likely nor Unlikely, Somewhat Unlikely, or Extremely Unlikely to Share in a Future Disaster

	Share Transportation Before			Share Transportation During			Share Shelter for Cost			Share Shelter for Free		
Variable	**Est. Coef.**	**p-value**		**Est. Coef.**	**p-value**		**Est. Coef.**	**p-value**		**Est. Coef.**	**p-value**	
Constant Share	-0.35	0.328		-1.26	0.007	**	-2.88	0.002	**	-0.70	0.139	
Individual Characteristics												
Young Adult (under 35)	-0.45	0.109		-0.66	0.031	*	------	-------		------	-------	
Female	-0.44	0.161		------	-------		0.70	0.169		------	-------	
Experienced 3 or More Hurricanes	------	-------		-0.57	0.032	*	------	-------		-0.31	0.140	
White	------	-------		------	-------		-1.36	0.003	**	-0.90	0.011	*
Previous Evacuee	------	-------		------	-------		0.76	0.033	*	------	-------	
Used Homesharing Before (e.g., Airbnb)	------	-------		------	-------		1.73	0.016	*	1.41	0.009	**
Household Characteristics												
Children Present in Household	-0.81	0.002	**	-0.45	0.090		-0.88	0.023	*	------	-------	
Residing in Southwest Florida	0.78	0.002	**	0.44	0.092		------	-------		------	-------	
Household Income $100,000 or More	-0.45	0.122		------	-------		-1.26	0.015	*	-0.40	0.088	
Person(s) with Disabilities in Household	-0.47	0.195		------	-------		------	-------		------	-------	
More than 10 Years in Residence	-0.92	0.021	*	------	-------		------	-------		------	-------	
Living in a Mobile Home	------	-------		-1.00	0.091		------	-------		------	-------	
Homeowner	------	-------		------	-------		-0.59	0.092		------	-------	
Live in FEMA Risk Zone [a]	------	-------		------	-------		0.65	0.058		------	-------	
Capacity												
Additional Seatbelts Available for Irma	------	-------		0.61	0.142		------	-------		------	-------	
Additional Spare Beds in House	------	-------		------	-------		1.07	0.090		0.41	0.188	
Evacuation Experience During Irma												
Evacuated Within County	0.50	0.120		0.87	0.006	**	------	-------		------	-------	
Evacuated with 2 or More Vehicles	0.54	0.058		------	-------		------	-------		------	-------	
Towed a Vehicle	------	-------		-0.46	0.224		------	-------		------	-------	
Observations	368			368			645			645		
R-squared	0.22			0.27			0.71			0.32		
Adjusted R-squared	0.18			0.24			0.68			0.30		
Log-Likelihood	-198.9			-185.8			-132.0			-306.2		
Null Log-Likelihood	-255.1			-255.1			-447.1			-447.1		
AIC	417.8			389.6			284.1			624.4		
BIC	456.8			424.8			328.8			651.2		

[a] Areas at risk of a 100-year flood defined by the Federal Emergency Management Agency (identified on the Flood Insurance Rate Map)

Significance: *** 99.9% ** 99% *95%

4.2 PCM Model Results

Given the limitations of isolated binary logit models, we next present results from the PCM, which captures joint preferences/dislikes. In the first model with only dimensions (Table 5), we found that all four primary dimensions (i.e., the four scenarios) were strongly negative. We subsequently found two statistically significant interactions: 1) Transport Before and Transport During and 2) Shelter Cost and Shelter Free. We note that this does not mean that an individual will choose to conduct both actions in an evacuation. Rather, there existed a joint preference in these scenarios.

Individuals had these joint preferences likely due to the scenario similarity and resource needs. For example, those who can share transportation before evacuating and during the evacuation likely have access to a vehicle with spare capacity to move people. Both scenarios are dependent on the same resource availability. Sharing transportation both before and during the evacuation also requires a similar amount of time to assist. The sharing is largely temporary – providing a ride for a short amount of time. The results also indicate that the *timing* of the assistance (either before or during the evacuation) does not lead to substantially different likelihoods to share. This is important, as officials can encourage sharing at different time points of the hazard. We also note that the joint preference could also reflect the respondents' similar risk perceptions of providing the assistance or even instinct qualities such as identify, trust, and compassion (see Borowksi et al. 2021 and Wong et al., 2020e for more discussion of these variables).

Regarding the joint preference for sharing shelter for a cost and shelter for free, a similar narrative arises. In particular, the two sheltering sharing scenarios are similar in the need for specific resources (i.e., beds, rooms) to provide the housing. This points to the prerequisite nature of capacity for sharing. The requirements for sharing shelter are also similar in terms of the number of days. Since length of stay was not specified in the scenario, respondents likely saw the length of stay as a fixed variable. The results also suggest that the *cost* of the shelter (charged by the respondent to the evacuee) does not lead to different likelihoods to share. In other words, those who wanted to share shelter at a cost would likely still share shelter for free. Enabling low or zero-cost shelter would significantly improve equity outcomes for lower-income and other disadvantaged populations. Finally, as noted in the transportation scenarios, the joint preference could also be influenced by similar intrinsic qualities (e.g., identity, trust, compassion).

For sharing transportation before evacuating (Table 5), long-time residents and individuals with children were less willing to share, which mirrors results in the binary logit model. Moreover, residents of Southwest Florida were more likely to share, perhaps for reasons shared previously. Low-income individuals (with annual income below $40,000) were also more likely to share transportation, which could relate to high empathy for carless individuals. This is similar to results by Borowski et al. (2021) which found that higher-income individuals were *less* willing to share rides to evacuees. Several evacuation circumstances (i.e., evacuating at night, receiving a mandatory evacuation order) were insignificant, but points to the potential use of these variables in future models using other collected data.

For sharing transportation during the evacuation, we found that long-time residents were more likely to share, which goes against the other models. In this case, long-term residents may have closer social networks proximity, which was found to increase ridesharing willingness in

Borowoski et al. (2021). Evacuating within county was also a positive variable, pointing to the extra time that people may have to help others (such as route deviation or additional travel time). Wong et al. (2020b), using the same data in this study, found that about 51% were willing to deviate a maximum of 30 minutes, but only 4% were willing to deviate more than one hour. On the other hand, low-income households and those with items to tow were less likely to share. Low-income individuals may be carless (as reviewed by Renne et al. 2011) or may have less vehicle space overall (due to fewer evacuating vehicles). Households with items to tow might not want to increase logistical challenges (e.g., maneuvering to pick up passengers).

For sheltering for a cost, we found several significant variables including high-income households (negative) and prior use of homesharing and receiving a mandatory evacuation order (positive). High-income individuals likely do not need additional income via homesharing. Interestingly, a similar result was found for ridesharing in Borowski et al. (2021) for flooding and Wong et al. (2020e) for wildfires. Previous users of homesharing likely understand the mechanisms of the platforms. For example, research on peer-to-peer accommodation stays found that those who had used homesharing before were more likely to use it again (Yang et al., 2019). Those who received a mandatory order may have experienced challenges finding their own housing.

Finally, for shelter for free, we only found one significant variable. Households with children were more likely to share shelter for free. This counterintuitive result is not immediately clear, as other models in this study have shown households with children to be less willing to share. However, Borowski et al. (2021) found that households with children to be more willing to rideshare, positing that compassion may be influencing this behavior. Wong et al. (2020e) also found that compassion (and trust) to significantly increase sharing willingness. Moreover, these households may also be displaying compassion to other households with children.

Table 5: PCM Results

	Primary + Interactions				Primary + Interactions + Demographics			
Variables	**Est. Coef.**	**Std. Error**	**p-value**		**Est. Coef.**	**Std. Error**	**p-value**	
Primary Dimensions								
Share Transport Before	-2.38	0.23	0.000	***	-2.47	0.46	0.000	***
Share Transport During	-4.20	0.48	0.000	***	-6.08	0.94	0.000	***
Share Shelter Cost	-3.75	0.40	0.000	***	-4.57	1.34	0.001	**
Share Shelter Free	-2.06	0.19	0.000	***	-2.00	0.65	0.002	**
Interactions								
Transport Before x Transport During	4.97	0.52	0.000	***	6.65	0.88	0.000	***
Transport Before x Shelter Cost	-0.13	1.08	0.905		-0.20	1.05	0.847	
Transport Before x Shelter Free	0.47	0.51	0.355		0.66	0.53	0.208	
Transport During x Shelter Cost	1.15	1.08	0.285		1.01	1.03	0.329	
Transport During x Shelter Free	1.01	0.52	0.051		0.99	0.53	0.064	
Shelter Cost x Shelter Free	1.88	0.49	0.000	***	2.04	0.52	0.000	***
Transport Before Variables								

Children Present in Household	-----	-----	------	-1.47	0.46	0.001	**
Residing in Southwest Florida	-----	-----	------	1.48	0.45	0.001	**
Annual Household Income Below $40,000	-----	-----	------	0.99	0.50	0.046	*
Living in Residence for 10+ Years	-----	-----	------	-2.95	0.89	0.001	**
Towed a Vehicle During Irma	-----	-----	------	0.92	0.54	0.087	
Evacuated at Night During Irma (6:00 pm - 5:59 am)	-----	-----	------	-0.86	0.65	0.185	
Received a Mandatory Evacuation Order During Irma	-----	-----	------	-0.53	0.44	0.233	
Transport During Variables							
Children Present in Household	-----	-----	------	0.82	0.49	0.093	
Residing in Southwest Florida	-----	-----	------	-0.77	0.48	0.104	
Annual Household Income Below $40,000	-----	-----	------	-1.20	0.55	0.030	*
Living in Residence for 10+ Years	-----	-----	------	2.37	0.86	0.006	**
Evacuated within County During Irma	-----	-----	------	0.84	0.32	0.008	**
Towed a Vehicle During Irma	-----	-----	------	-1.25	0.58	0.031	*
Evacuated at Night During Irma (6:00 pm - 5:59 am)	-----	-----	------	1.16	0.65	0.077	
Received a Mandatory Evacuation Order During Irma	-----	-----	------	0.86	0.47	0.067	
Shelter Cost Variables							
White (race)	-----	-----	------	-0.91	0.73	0.213	
Children Present in Household	-----	-----	------	-0.83	0.52	0.113	
Annual Household Income $100,000 or Above	-----	-----	------	-1.22	0.49	0.013	*
Additional Spare Beds in House	-----	-----	------	1.73	1.05	0.100	
Used Homesharing Before (e.g., Airbnb)	-----	-----	------	1.91	0.83	0.021	*
Received a Mandatory Evacuation Order During Irma	-----	-----	------	1.30	0.56	0.021	*
Shelter Free Variables							
White (race)	-----	-----	------	-0.75	0.56	0.179	
Children Present in Household	-----	-----	------	0.62	0.31	0.041	*
Annual Household Income Below $40,000	-----	-----	------	0.59	0.44	0.182	
Annual Household Income $100,000 or Above	-----	-----	------	0.67	0.35	0.051	
Used Homesharing Before (e.g., Airbnb)	-----	-----	------	1.11	0.72	0.124	
Received a Mandatory Evacuation Order During Irma	-----	-----	------	-0.49	0.30	0.104	
Observations	368			368			
Parameters	10			37			
R-Squared	0.44			0.49			
Adjusted R-Squared	0.43			0.46			
Log-Likelihood	-545.4			-492.6			
Log-Likelihood Null	-971.2			-971.2			
AIC	1110.7			1059.2			
BIC	1149.8			1203.8			

Significance: *** 99.9% ** 99% *95%

4.3 Multi-Choice LCCM Model Results

The PCM results help establish clearer joint preference between sharing options. However, the model fails to identify if there is heterogeneity in the population and if different classes of people exist who have different sharing preferences. We next present the results of the multi-choice LCCM model (Table 6) via four choice models and one membership model. We tested several variables for the choice-specific models (e.g., receiving a mandatory evacuation order, spare beds), but only spare seatbelts was significant. After testing two and four classes, we found that three classes offered the most reasonable goodness of fit, statistical significance of variables, and behavioral interpretation.

4.2.1 Class 1 – Adverse Sharer

This class of individuals was highly unwilling to share resources in any scenario and are named "adverse sharers." This is evidenced by the negative and significant Class 1 constant signs for all scenarios. Class 1 also displayed some selfish behavior, as those with additional seatbelts in their vehicle were less likely to share transportation before or during the evacuation. These individuals may view extra seatbelts as space for belongings, a response that could be amplified by social cues from other people attempting to protect their belongings (see Lindell and Perry, 2011 on protective actions). Individuals were more likely to be members of Class 1 over Class 2 and Class 3, all else equal (based on the constants in the membership model).

4.2.2 Class 2 – Transportation Sharers

This class of individuals was generally willing to share transportation both before and during an evacuation based on the positive constants for Class 2, hence a class of "transportation sharers." Additional seatbelts were insignificant in influencing willingness to share for this class (though it was positive). This class exhibited strong aversion to sharing shelter, as seen with the negative and significant constants for both sheltering scenarios. This reflects the PCM model results that found a strong joint preference for the two transportation sharing scenarios. Significant membership was only composed of residents from Southwest Florida. Individuals from Southwest Florida were heavily impacted by Hurricane Irma, perhaps leading to higher empathy. As noted in the binary logit models, Southwest Florida includes the Florida Keys, which present significant transportation challenges while evacuating. We note that several insignificant variables were found to have a higher likelihood to be part of the class (i.e., females and higher-income individuals), though more work with a different sample is necessary to determine significance.

4.2.3 Class 3 – Interested Sharers

This class of individuals was general more willing to share resources across all scenarios, but the constants across scenarios were mostly insignificant. However, Class 3 exhibited stronger sheltering sharing behavior. Thus, Class 3 might be considered as "interested sharers" as concerns may exceed sharing willingness. In this class, we failed to identify any significant demographics that provide membership to the class. However, we did notice that the constant to be a part of the class was negative and significant, indicating that people are generally *not* interested sharers. This result suggests that there might be a clear bifurcation among the sample: those who do not want to share and those who will share transportation only.

Table 6: Multi-Choice LCCM Model Results

Class 1: Adverse Sharers
Class 2: Transportation Sharers
Class 3: Interested Sharers

Share Transportation Before	**Est. Coef.**	**p-value**	
Constant Class 1	-2.24	<0.001	***
Constant Class 2	2.03	0.018	*
Constant Class 3	0.37	0.421	
Additional Seatbelts During Irma - Class 1	-1.21	0.049	*
Additional Seatbelts During Irma - Class 2	1.41	0.114	
Additional Seatbelts During Irma - Class 3	0.72	0.335	
Share Transportation During	**Est. Coef.**	**p-value**	
Constant Class 1	-2.59	<0.001	***
Constant Class 2	0.44	0.243	
Constant Class 3	0.39	0.416	
Additional Seatbelts During Irma - Class 1	-1.62	0.037	*
Additional Seatbelts During Irma - Class 2	1.12	0.056	†
Additional Seatbelts During Irma - Class 3	0.87	0.330	
Share Sheltering for Cost	**Est. Coef.**	**p-value**	
Constant Class 1	-3.22	<0.001	***
Constant Class 2	-2.27	<0.001	***
Constant Class 3	0.55	0.141	
Share Sheltering for Free	**Est. Coef.**	**p-value**	
Constant Class 1	-1.96	<0.001	***
Constant Class 2	-0.69	<0.001	***
Constant Class 3	1.39	0.012	*
Membership Model	**Est. Coef.**	**p-value**	
Constant Membership - Class 2	-1.27	0.207	
Constant Membership - Class 3	-1.87	0.029	*
Living in Southwest Florida - Class 2	0.98	0.001	***
Living in Southwest Florida - Class 3	-0.35	0.159	
Children Present in Household - Class 2	-0.70	0.210	
Children Present in Household - Class 3	-0.76	0.304	
Female - Class 2	0.35	0.132	
Female - Class 3	-0.35	0.323	
Living in Residence for More than 10 Years - Class 2	-0.67	0.092	†
Living in Residence for More than 10 Years - Class 3	0.33	0.232	
Annual Household Income $100,000 or More - Class 2	0.05	0.088	†
Annual Household Income $100,000 or More - Class 3	-0.97	0.110	
Number of Observations	368		
Number of Parameters	30		
R-Squared	0.67		
Adjusted R-Squared	0.65		
Log-Likelihood	-535.9		
Log-Likelihood Null	-1617.2		
AIC	1131.8		
BIC	1249.0		

Significance: *** 99.9% ** 99% *95% †90%

4.4 Modeling Discussion

Through our modeling exploration, we found distinct benefits and limitations of each model type (see Table 7 for a summary). We first developed simple binary logit models, focusing on each scenario separately. However, this simplicity belies scenario correlation. Consequently, we explored two joint discrete choice models: 1) PCM and 2) a multi-choice LCCM. Relatively easy to estimate as a multinomial logit model (after a more challenging development of portfolios), the PCM identified correlation between scenarios and clearly defined provider groups. However, we found that more parameters in the PCM, while mostly significant, did not improve model fit, and the model failed to identify classes of individuals. With these limitations, a multi-choice LCCM was constructed to connect the different scenarios, identifying unique classes of people. We found three classes, each with its own set of members. This categorization helps identify that some people are sharing adverse and will be unlikely to help in a disaster, regardless of the scenario. Results also uncover that some individuals may require additional nudges to encourage sharing behavior. Despite these more nuanced results, we do lose some details of provider groups due to the multi-choice LCCM structure. Moreover, the multi-choice LCCM is sensitive to a high parameter to sample size ratio and the number of latent classes.

Table 7: Comparison of Model Types

	Binary Logit Model	**Portfolio Choice Model**	**Multi-Choice Latent Class Choice Model**
Insights	Identifies simple relationships, especially helpful for policy development	Identifies joint preferences/dislikes among choices	Identifies heterogeneity based on joint preferences/dislikes
Joint (Multi-Choice) Analysis	No	Yes	Yes
Ease of Interpretation	Easy to understand and describe	Moderately hard to understand and describe	Hard to understand and describe
Modeling Difficulty	Easy (coding packages available)	Moderate (requires transformation of choices into portfolio)	Moderate (requires coding beyond currently available coding packages)
Variable Selection	Straightforward (use standard procedures found in literature)	Straightforward (use standard procedures found in literature)	Challenging (inclusion of different demographics in the membership model can have large effects of coefficients and significance)
Limitations	Does not consider choices together or heterogeneity in the population	Fails to determine *why* certain joint preferences/dislikes exist or heterogeneity in the population	Requires a large sample size and is highly sensitive to the inclusion of new variables

Several key takeaways can be gleaned from the behavioral results. First, we found that correlation exists between scenarios, which means that there is an underlying relationship between sharing scenarios. The PCM and multi-choice LCCM clearly identified that scenarios were correlated, and the two transportation scenarios were strongly linked. The two shelter scenarios were also linked, but we found unconvincing results of the correlation between the transportation and shelter scenarios. We note that the link between the transportation scenarios and between the shelter scenarios may be related to similar resource requirements. Both transportation sharing scenarios require a vehicle while both shelter sharing scenarios require a bed/mattress. The transportation sharing scenarios are also largely temporary, producing a different required action than sheltering, which is more long-lasting (i.e., multi-day stays). This might help explain why an individual may be willing to share transportation strongly in the multi-choice LCCM, but not sheltering: sharers only have to transport individuals over a set amount of time (e.g., a few hours). Interestingly, our variation of the scenario (different time points for transportation and different fees for sheltering) did not appear to alter the joint preferences involved. This is encouraging, as agencies might want to focus on one time period of the disaster to transport people (such as before the evacuation begins to reduce risk) or one fee structure for sheltering (such as for free to reduce costs for disadvantaged evacuees). Moreover, the multi-choice LCCM clearly found a group of adverse sharers who were unwilling to share across any sharing scenario. This result is also helpful: agencies should prioritize nudging interested sharers and transportation sharers through strategies (outlined extensively in Wong et al. 2020a) to gain modest increases in resources without significant barriers. While more work is needed to better identify *who* is a part of each class (given mostly insignificant variables), their existence is a strong first step in crafting more targeted strategies to increase sharing. Moreover, the multi-choice LCCM (unlike the PCM) identified a stronger correlation between the transportation sharing scenarios compared to the sheltering scenarios. This suggests that transportation sharers may be more motivated to assist, offering opportunities to help disadvantaged populations in evacuations.

Regarding results beyond joint preferences, we found that households with children were generally unwilling to share. In almost all models and scenarios, households with children were less willing to provide resources. This result likely stems from concerns about their children's safety and security, which was also found in Wong et al. (2020e) and Brodar et al. (2020). Third, spare capacity had positive but mostly insignificant influence on sharing. While capacity is a prerequisite for sharing, it is not a primary motivator for sharing. Messaging to make space available for evacuees is unlikely to nudge evacuees into sharing. Fourth, income had uneven impacts on willingness to share with unclear directionality for low-income and high-income individuals. Some (but not all) results mirrored work by Borowski et al. (2021), which found that higher-income individuals were less likely to share. Our hypothesis for these variations in results is that variables related to intrinsic value or community resilience (e.g., compassion, trust, social capital) could be at play. The model construction might also affect the results – heterogeneity might exist within a single income bracket (as evidenced by the multi-choice LCCM). The simpler binary logit model may only be capturing general behavior for the income level.

Fifth, users of homesharing were more willing to share shelter for a cost and for free. While the homesharing variable was not significant for the multi-choice LCCM, the other modeling results indicate a potential opportunity to increase sheltering resources. The lack of significance in the multi-choice LCCM might be because of the model's limitations: it did not identify a "shelter sharer" group and the model exhibits sensitivity to a high parameter to sample size ratio. Sixth, transportation sharing was affected by different factors – individual characteristics, household characteristics, evacuation circumstances – but the significance was not consistent across models or scenarios. The results suggest that transportation sharing may be context-dependent, requiring a triggering mechanism (Wong et al., 2020e). Otherwise, the result could be influenced again by model construction. The inclusion of correlation structures likely plays a role in the significance of some variables over others. We argue here that building all three model types enabled us to find some inconsistency, when a single model would have prompted a stronger (perhaps inaccurate) conclusion.

Most demographic variables (e.g., age, race, education, gender) were somewhat weak and sporadic indicators of sharing. This "non-result" indicates that other variables (e.g., social capital, trust, compassion, social network) may be stronger drivers of sharing behavior. Wong et al. (2020e) found that trust and compassion and evacuation urgency influenced willingness to share for future wildfires. Sadri et al., (2018) found that social capital and social networks were tied to post-disaster recovery, and Sadri et al. (2017b) found that social networks influenced evacuation decision-making. These studies and this work suggest that increasing shared resources in disasters should focus more on internal motivations.

Finally, we note that the models sometimes produced contradictions. As described previously, income decreased willingness to share in some models and increased willingness to share in other models. Demographic variables were often sporadic in significance and inconsistent in directionality of influence. Previous evacuation experience during Hurricane Irma (and other disasters) also produced inconsistencies across models. These insights shed light on how different models can produce different results. The purpose, construction, and limitations of each model can lead to different effects and variable importance. Ultimately, the inconsistencies provide some caution for modelers – the model selection process can produce misleading results, similar to the variable selection process.

4.5 Pandemic Limitations

These modeling results and conclusions come with an important caveat. Social distancing and stay-at-home orders during the COVID-19 pandemic have significantly altered the sharing economy sector (Shaheen and Wong, 2021). While shared mobility and sheltering is often a final option for resource-strapped evacuees, concerns about COVID-19 exposure and spread (Pei et al., 2020) only increase the likelihood that shared resources are a last-resort alternative in an evacuation. Consequently, results provided here pertain to a past and potential future without a pandemic. However, steps can be taken to reduce virus exposure and spread in evacuations as noted in Pei et al., (2020). Future work will be necessary to ensure that shared mobility and public transit are still available to evacuees during pandemics beyond the COVID-19 pandemic.

Moreover, any future work on the sharing economy and evacuations should consider the long-lasting role of the pandemic on the willingness to share resources in disasters. For example, Borowski et al. (2021) found that those that perceived the COVID-19 pandemic as a strong threat to their health were less likely to share transportation during a flood evacuation. While the research found that other variables (such as race, age, income, and political preference) to have stronger marginal effects on sharing willingness in an evacuation, long-term concerns over sharing due to the pandemic may remain for disasters. Proactive measures to mitigate COVID-19 spread (e.g., mask wearing, better air filtration, enhanced cleaning) as described in Wong et al. (2020f) could alleviate some of the concerns. This is especially important, given that Borowski et al. (2021) found that people were most concerned about their driver wearing a mask (over background checks, navigational skills, and driver ratings). Future work should continue to ask people about their remaining COVID-19 concerns while sharing in a disaster.

5. RECOMMENDATIONS AND CONCLUSION

Finally, we present several intuitive recommendations. First, we recommend that a transportation sharing strategy should be temporally inclusive (i.e., allow sharing before, during, and after the disaster). Modeling results indicate significant correlation between transporting passengers before and during the evacuation. For example, an individual who is willing to share before evacuating but is unable due to evacuation circumstances may still share during or after the evacuation. Second, public agencies should combine transportation and sheltering strategy into a broader program (i.e., evacuee assistance program) that offers multiple opportunities to assist. The PCM found mostly positive interactions among scenarios, indicating joint preference. The multi-choice LCCM found a class of interested sharers who could be nudged to share across scenarios via a more broader multi-resource assistance program. Moreover, a more comprehensive program could nudge interested sharers (and transportation sharers) to provide resources beyond transportation and sheltering (i.e., food, supplies, monetary assistance). Finally, agencies should partner with and leverage existing homesharing platforms (e.g., Airbnb, VRBO) to increase willingness to share sheltering. Users of homesharing were more willing to share shelter in the binary logit models and the PCM, perhaps due to their experience with renting and sharing housing.

This research represents a key step into building a sharing economy framework for disasters. We developed three sets of discrete choice models – four binary logit models, a portfolio choice model (PCM), and a multi-choice latent class choice model (LCCM) – for sharing willingness using data from evacuees of Hurricane Irma in 2017 (n=368). We first constructed four binary logit models to independently assess how factors impacted scenarios separately. However, we hypothesized that the responses to the sharing scenarios were correlated, so we next developed a PCM that identified significant dimensional dependency between scenarios. We next developed a multi-choice LCCM, which captures classes of individuals across multiple choices. We found three unique classes of individuals – 1) adverse sharers, 2) interested sharers, and 3) transportation-only sharers – each with different demographic membership. However, these demographic variables were somewhat weak, mirroring results in the other model types. Altogether, this multi-model analysis uncovered more behavioral nuances than a single model approach. Moreover, a multi-model approach encouraged an exploration of the benefits and limitations of different models, without assuming superiority of one model over another.

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7. CONTRIBUTIONS

Study conception and design: S. Wong, M. Yu , J. Walker, and S. Shaheen; data collection: S. Wong; analysis and interpretation of results, draft manuscript preparation, results review, approval: all authors.

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