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Stephen D. Wong

Adam J. Pel

Susan A. Shaheen

Caspar G. Chorus

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Stephen D. Wong (**Corresponding Author)**
Department of Civil and Environmental Engineering
University of California, Berkeley
116 McLaughlin Hall, Berkeley, California, United States
Tel: 1-330-998-4533
stephen.wong@berkeley.edu

Adam J. Pel
Faculty of Civil Engineering and Geosciences
Delft University of Technology
Building 23, Stevinweg 1, Delft, the Netherlands
Tel: 31-15-27-84874
a.j.pel@tudelft.nl

Susan A. Shaheen
Transportation Sustainability Research Center
University of California, Berkeley
408 McLaughlin Hall, Berkeley, California, United States
Tel: 1-510-642-9168
sshaheen@berkeley.edu

Caspar G. Chorus
Faculty of Technology, Policy, and Management
Delft University of Technology
Building 31, Jaffalaan 5, Delft, the Netherlands
Tel: 31-15-27-88546
C.G.Chorus@tudelft.nl

Highlights:

- Latent class choice model finds evacuation-keen and -reluctant classes for evacuation decision.
- Evacuation-reluctant class is impacted by mandatory orders, necessitating targeted orders.
- Portfolio choice model estimates multi-dimensional choices without imposing hierarchy.
- Modeling finds strong dependency among evacuation choice dimensions.
- Joint preferences for dimensions and demographic variables are highly significant.

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ABSTRACT

This paper analyzes the observed decision-making behavior of a sample of individuals impacted by Hurricane Irma in 2017 (n = 645) by applying advanced methods based in discrete choice theory. Our first contribution is identifying population segments with distinct behavior by constructing a latent class choice model for the choice whether to evacuate or not. We find two latent segments distinguished by demographics and risk perception that tend to be either evacuation-keen or evacuation-reluctant and respond differently to mandatory evacuation orders.

Evacuees subsequently face a multi-dimensional choice composed of concurrent decisions of their departure day, departure time of day, destination, shelter type, transportation mode, and route. While these concurrent decisions are often analyzed in isolation, our second contribution is the development of a portfolio choice model (PCM), which captures decision-dimensional dependency (if present) without requiring choices to be correlated or sequential. A PCM reframes the choice set as a bundle of concurrent decision dimensions, allowing for flexible and simple parameter estimation. Estimated models reveal subtle yet intuitive relations, creating new policy implications based on dimensional variables, secondary interactions, demographics, and risk-perception variables. For example, we find joint preferences for early-nighttime evacuations (i.e., evacuations more than three days before landfall and between 6:00 pm and 5:59 am) and early-highway evacuations (i.e., evacuations more than three days before landfall and on a route composed of at least 50% highways). These results indicate that transportation agencies should have the capabilities and resources to manage significant nighttime traffic along highways well before hurricane landfall.

Key Words: Evacuations, evacuee behavior, portfolio choice model, latent class choice model, Hurricane Irma

1. Background and Literature

In 2017, the United States (U.S.) was severely impacted by a number of devastating natural disasters that required mass evacuations. Of these disasters, Hurricane Irma in September 2017 led to one of the largest evacuations in U.S. history, involving over six million people (National Oceanic and Atmospheric Administration, 2018; Maul, 2018). Officials in Florida issued mandatory evacuation orders in 54 of 67 counties in the state to 6.8 million people, leading to the largest evacuation in Florida history (Maul, 2018). The unique characteristics of this disaster situation presented an extremely challenging scenario for officials as they attempted to adequately transport and shelter citizens. With varying trajectories and projections, the Florida State Emergency Response Team planned over a dozen potential impact scenarios at the same time (Maul, 2018). Despite these challenges, Florida was able to house over 190,000 people in public shelters during Hurricane Irma and deliver over 1.4 million gallons of fuel to assist with the evacuation and first responder recovery efforts (Maul, 2018). This large-scale operation for Hurricane Irma is by no means an exception. Other large hurricanes in 2017 and 2018 including Hurricanes Harvey, Maria, Florence, and Michael prompted large-scale evacuations or mass rescue efforts. Large wildfires in California including the October 2017 Northern California Wildfires, the December 2017 Southern California Wildfires, 2018 Camp Fire, and 2018 Woolsey Fire forced the evacuation of hundreds of thousands of individuals. With growing populations in high-risk areas and increased disasters due to climate change, the size and scope of evacuations will continue to rise. Consequently, the behavior of evacuees (and non-evacuees) is becoming an increasingly important consideration for transportation management throughout the evacuation process. For example, evacuees often decide to depart around the same time, leading to heavy traffic congestion.

The behavior of individuals during evacuations has long been established using descriptive statistics (Gruntfest, 1977; Baker, 1979; Greene et al., 1981; Leik et al., 1981; Cutter and Barnes, 1982; Perry et al., 1982; Zeigler and Johnson, 1984; Stallings, 1984; Baker, 1990; Baker, 1991; Drabek, 1992; Dow and Cutter, 1998). To expand on this descriptive work and determine the driving factors behind such behavior, many studies have developed discrete choice models (DCMs). These “first-generation” DCMs use binary or multinomial logit structures to show the effect of demographic characteristics, storm characteristics, and risk perceptions on evacuation choices. Studies of multiple choices have been conducted including the decision of whether to evacuate or not (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), departure timing (Fu and Wilmot, 2004; Fu et al., 2006; Dixit et al., 2012; Wong et al., 2018), destination (Cheng et al., 2008; Wong et al., 2018), shelter type (Whitehead et al., 2000; Smith and McCarty, 2009; Deka and Carnegie, 2010; Wong et al., 2018), transportation mode (Deka and Carnegie, 2010; Wong et al., 2018), and route (Akbarzadeh and Wilmot, 2015; Wong et al., 2018). Soon after, researchers expanded upon these first-generation DCMs by employing methods to capture unobserved heterogeneity in the population, correlation among alternatives in the choice-set, and model uncertainty. These “second-generation” DCMs, long-established in the transportation field include: mixed logit, probit, nested logit, and other random-parameter models to capture evacuation choices (Deka and Carnegie, 2010; Solis et al., 2010; Hasan et al., 2011; Xu et al., 2016; Yin et al., 2016), departure timing (Gudishala and Wilmot, 2012; Hasan et al., 2013; Sarwar et al., 2018), shelter type (Mesa-Arango et al., 2012), transportation mode (Sadri et al., 2014a), and route (Sadri et al., 2014b; Sadri et al., 2015).

In light of current literature, two key gaps remain of which the last one is the most important. The first is the identification of latent population segments with distinct behavior. The identification of so-called latent classes is well established for other transport applications (Walker and Li, 2007; Carrel et al., 2011; Hensher and Greene, 2010; Wen and Lai, 2010; Vij et al., 2013; El Zarwi et al., 2018), where latent class choice models (LCCMs) distinguish heterogeneous subpopulations based on lifestyle preferences, for example. Despite their limited use in describing evacuee behavior (Urata and Pel, 2018; McCaffrey et al., 2018), LCCMs have the power to add new behavioral insights on evacuation choices by identifying classes of evacuees. Urata and Pel (2018) found risk recognition to be a key factor in evacuation choice for tsunamis, allowing the quantification of different policy mechanisms such as: risk mitigation, risk education, and risk information on choice and class. McCaffrey et al. (2018) also focused on risk characteristics for wildfire evacuee classes, finding that different belief attitudes, warnings, and environmental cues impacted the decision to evacuate or stay and defend. Despite this literature, latent class choice models have yet to be developed for hurricane evacuations in order to identify how specific groups respond to evacuation orders.

Second, different dimensions (such as route and departure time) of evacuation choices are traditionally analyzed in isolation (as seen in Wong et al., 2018; Deka and Carnegie, 2010), instead of as the joint, multi-dimensional choice that may be faced by an individual or household. Recent studies in the hurricane evacuation literature have attempted to consider two choice dimensions either sequentially or jointly. Fu and Wilmot (2004) and Fu et al. (2006) developed a sequential logit model that combined the decision whether or not to evacuate and departure timing, finding that storm characteristics (i.e., wind speed); evacuation orders; time of day; evacuation zone; and housing characteristics were significant in the joint model. Gudishala and Wilmot (2012) relaxed assumptions regarding ordering of the choice dimensions (i.e., which choice is made first) by developing a time-dependent nested logit model. Their model had better predictive capability than the sequential logit model, but it found similar characteristics impacting choice with the addition of income and vehicles owned. Bian (2017) jointly estimated transportation mode and destination type through a nested logit model, finding clear links between the two choices across several hurricane datasets. The generalizability of joint estimation further indicates the need for these model types across other choices. Indeed, Gehlot et al. (2018) estimated a joint discrete-continuous departure model for departure timing and travel times, finding significant correlation between the choice dimensions. Despite these strong strides in understanding the relationship among choice dimensions, no study to date has captured the full multi-dimensional choice composed of the concurrent decisions on departure day, departure time of day, destination, shelter type, transportation mode, and route. Such multi-dimensionality demands new modeling approaches for this much-needed "third-generation" of evacuation DCMs, which handle joint decision making.

To solve these gaps (i.e. accounting for latent classes in evacuation behavior, and the joint multi-dimensional nature of evacuation choices), we collected and analyzed empirical data from October to December 2017 on the decisions made by individuals affected by Hurricane Irma through an online survey (n=645) (Wong et al., 2018). We use these data to identify distinct subpopulations based on their demographics and risk perceptions by means of an LCCM for the choice to evacuate or not in a hurricane context. This LCCM structure provides additional behavioral insights compared to earlier second-generation DCMs by considering the role of mandatory evacuation orders as a class-specific variable. Second, we use these empirical data to develop and apply a portfolio choice model (PCM) (Van Cranenburgh et al., 2014a), which captures the full multi-dimensional choice of evacuees, taking into account crucial and overlooked dependencies between different choice dimensions. To our knowledge, this is the first paper to: 1) model the full multi-dimensional and interdependent nature of evacuee choices; 2) apply a PCM for evacuation behavior; and 3) advance an LCCM using revealed preference hurricane evacuation behavioral data. To supplement these empirical and methodological contributions, we also generate and discuss several new behavioral insights that can be applied to improve evacuation strategies.

2. Data

Hurricane Irma was a powerful hurricane that severely impacted multiple islands in the Atlantic Ocean before making landfall in Florida. The storm had one of the strongest sustained wind speeds on record and longest time sustained as a Category 5 hurricane (National Oceanic and Atmospheric Administration, 2018). Before Irma made landfall as a Category 4 hurricane, forecasters were uncertain if the storm would impact the western or eastern coastline. Ultimately, Hurricane Irma first made landfall in Cudjoe Key, Florida in the west on September 10 with a second landfall on Marco Island, Florida later that day. This variable storm trajectory led officials to issue numerous mandatory and voluntary evacuation orders across Florida.

Given this unique storm, we developed an online survey to collect information on the individual choices of those impacted by Hurricane Irma. We distributed a 146-question survey from October to December 2017 with the assistance of local emergency management, transportation, public transit, planning, and non-governmental agencies. Agencies were chosen based on their proximity to the storm and jurisdiction size. Agencies were encouraged to use a variety of online distribution methods including: Facebook, agency websites, Twitter, alert subscription services, and newspapers. We encouraged agencies to notify other Florida agencies that may be interested, thus adopting a snowball technique. We distributed the survey across a wide geography and through multiple outlets to increase its coverage to the general population. We incentivized the survey through a lottery opportunity to win one of five $200 gift cards. The survey elicited 921 completed surveys from 1,263 respondents (74% completion rate). We retained 645 cleaned surveys for modeling by keeping surveys that answered all demographic questions and choice questions. Surveys with incomplete answers are unusable for discrete choice modeling, and we opted against data imputation, which requires significant assumptions of the sample and associated population. Of the 645 respondents, 368 respondents evacuated while 277 respondents did not evacuate. The LCCM model uses all 645 responses since both evacuees and non-evacuees made the decision to evacuate or stay. However, only evacuees (n=368) were used to estimate the PCM, since we do not know the evacuation choices of non-evacuees. Table A1 in the Appendix provides the respondents' demographic information, Table A2 displays the cross tabulation of the decision to evacuate or stay and receiving a mandatory evacuation order, and Table A3 provides the descriptive statistics for the key evacuation choices (Wong et al., 2018). We note that of those who received a mandatory evacuation order, 69.5% evacuated and 30.5% did not evacuate. This is similar to other results from a telephone poll of registered voters in Florida that found the split for those given mandatory orders to be 57% evacuated and 43% not evacuated (Mason-Dixon Polling and Research 2017). The same poll found that 32% of Florida residents evacuated, which is significantly different from 57% who evacuated from our sample. This is largely a result of our targeted distribution to counties that were issued evacuation orders and/or were impacted by Hurricane Irma. This convenience sample does not allow us to make any conclusions on future evacuation rates in Florida nor do we claim that our survey of impacted individuals is representative of Florida as a whole.

We also note that we employed an online survey to quickly and cost effectively reach a broader population of individuals impacted by Hurricane Irma. The online methodology enabled a more complex survey with substantial skip logic that reduced survey dropouts. We acknowledge that online surveys have clear limitations, particularly with respect to selection and sampling bias. We attempted to reduce selection and sampling bias by offering an incentive and distributing the survey via multiple types of agencies across numerous media platforms. Despite these attempts, survey respondents were still mostly white (94.0%), highly educated (93.5% with some college or more), female (81.9%), and higher income (30.1% with household income of $100,000 or more). We oversampled these individuals in comparison to Florida (75.7% white, 58.7% with some college or college, 51.1% female, and 20.9% with household income of $100,000 or more) (American Community Survey, 2017). Oversampling was most likely due to targeting survey distribution along the predominately wealthier coastlines of Florida (which were impacted by Hurricane Irma) and employing an online survey that requires Internet access. Despite the sampling bias, we note higher age variation, employment status, household size, housing type, length of residence, and hazard experience. In addition, the primary contributions of this work are methodological (i.e., developing and estimating evacuation behavior models). Improvements in survey design and sampling of individuals impacted by disasters remains a challenge in the evacuation field, and future surveys should address some of these challenges.

3. To Evacuate or Not: Development and Application of Latent Class

Latent classes capture population segmentation into specific classes that are not directly observed or measured, but they show distinct behaviors. LCCM applications in transportation and travel behavior have found the influence of latent differences in lifestyles on behavior (Walker, 2001; Greene and Hensher, 2003; Greene and Hensher, 2013). LCCMs have also been used to study the evacuation behavior and risk recognition of tsunami evacuees (Urata and Pel, 2018) and wildfire evacuees (McCaffrey et al., 2018) on the decision to evacuate or not. We add to this growing literature by identifying distinct classes of individuals using an LCCM for the decision to evacuate in a hurricane evacuation, which is the most widely studied evacuation choice in the most widely studied hazard.

The LCCM is composed of two models: 1) a class-specific DCM and 2) a class-membership model. The class-specific DCM describes the behavioral choice of individuals who belong to a particular class; it contains alternative-specific variables (i.e., attributes) that reflect the choice context. In the case of our LCCM, only a variable for receiving a mandatory evacuation order is included, since it is not an inherent quality of the decision maker. The class-membership model is composed of socio-demographics and respondent risk perception variables. Coefficients reflect, for each variable, the increased or decreased probability of being part of a class for different variable values, as such distinguishing each class composition. We note that by including mandatory evacuation orders as a class-specific variable, our LCCM extends previous work on evacuee behavior that considered mandatory evacuation orders as part of the class-membership model (Urata and Pel, 2018; McCaffrey et al., 2018). For a more detailed description of the LCCM methodology, the Appendix includes the formulation for the class-specific and membership models. We estimate the LCCM through an expectation-maximum algorithm using the Python package LCCM (El Zarwi et al., 2018). For this model, we use the entire Hurricane Irma sample of 645 responses, which includes both evacuees and non-evacuees. The choice in this LCCM model is a binary decision: 1) the respondent evacuated and 2) the respondent did not evacuate. We asked respondents: “Did you and your household evacuate your residence due to Hurricane

Irma?" and respondents either answered "yes" or "no." In this revealed preference setting, we note that some individuals may have been physically or financially unable to evacuate. Other individuals may have run out of time to evacuate. All of these individuals, regardless of *evacuation ability*, appear in our model as non-evacuees, which is a limitation. We note that future work in the field could further subdivide non-evacuees based on these characteristics. We also note that our LCCM model did not find any unique class of individuals with differing evacuation ability. Furthermore, exploration using this model with other data may be necessary.

The results for the LCCM model are provided in Table 1. Estimated coefficients indicate the utility derived from a unit increase in attribute value of the variable. Since all variables are dummy variables, the estimated coefficient is the utility (or disutility) from responding in the affirmative ("1") for that variable. P-values represent variable significance, and lower p-values indicate a higher level of confidence that the variable has a real effect on choice behavior. Several variables are included in the model that had relatively high p-values, indicating insignificance. These variables are retained as they are commonly assessed in the evacuation behavior literature (e.g., gender, children in the household, pets in the household). We also estimate a simple binary logit model (Table A4) using the Python package *Pylogit* (Brathwaite and Walker, 2018). LCCMs are a clear extension of binary logit models and add behavioral insights that are not readily apparent in the binary logit model. Thus, the binary logit model is a baseline model for behavioral comparison and represents a first-generation model that is still widely employed in the field.

3.1 Latent Class Choice Model Results

For the decision to evacuate or not, we identified two distinct classes of individuals from our sample of both evacuees and non-evacuees through the probabilistic LCCM model (Table 1). The first class contained individuals who were inherently less likely to evacuate (reflected by a negative intercept), but they were positively influenced by receiving a mandatory evacuation order. We name this class "Evacuation-Reluctant." Approximately 45% of the sample was estimated to belong to this class, of which about 15% evacuated. The other 85% of the class did not evacuate. Thus, mandatory evacuation orders played a role in encouraging some evacuations, but most of the class still decided to stay (hence the reluctancy). The second class contained individuals who were inherently more likely to evacuate (reflected by a positive intercept) and were not influenced by the mandatory evacuation order. We name this class "Evacuation-Keen." Of the 55% of the sample estimated to belong to this class, about 92% evacuated.

For the class-membership model, the socio-demographics mirror those in the simple binary model, which provides a strong LCCM sign validity. Positive values indicate a higher likelihood to be part of the evacuation-keen class. Risk variables including "worry of Irma severity," "belief of major structural damage," and "belief of injury or death" were all positive and significant. This indicates that individuals with higher risk perceptions have a stronger tendency to evacuate, but they were minimally impacted by receiving a mandatory order. However, those who perceived logistical challenges such as: "worry in finding housing," "finding gas," "housing costs," and "work requirements" were more likely to be evacuation-reluctant, but they may be persuaded by an evacuation order. In general, females, people with pets, previous evacuees, and long-time residents were more likely to be evacuation-reluctant, while families with children and those living in Southwest Florida (where Irma made landfall) were more likely to be evacuation-keen.

Table 1 Latent Class Choice Model: Evacuate or Not (n=645)

Class 1 Model (45.6%) - 15.5% evacuate – Evacuation-Reluctant	**Estm. Coef.**	**p-value**	
Constant Class 1	-2.93	<0.001	***
Received a Mandatory Order	1.97	0.002	**

Class 2 Model (55.4%) - 92.2% evacuate – Evacuation-Keen	**Estm. Coef.**	**p-value**	
Constant Class 2	2.50	<0.001	***
Received Mandatory Order	-0.05	0.934	
Class-Membership Model (Class 2)	**Estm. Coef.**	**p-value**	
Class-Specific Constant	0.83	0.127	
Concerns and Worry			
Extreme Likelihood Belief of Major Structural Damage	2.21	<0.001	***
Extreme or Somewhat Likelihood Belief of Injury/Death	2.11	<0.001	***
Extreme Worry of the Severity of Irma	1.69	<0.001	***
Extreme or Somewhat Worry of Finding Gas	-0.50	0.159	
Extreme Likelihood Belief of Work Requirements	-0.89	0.010	**
Extreme Worry of Finding Housing	-0.94	0.052	
Extreme or Somewhat Worry of Housing Cost	-1.28	0.005	**
Individual Characteristics			
Female	-0.48	0.245	
Previous Evacuee	-1.31	<0.001	**
Household Characteristics			
Living in Southwest Florida	1.69	<0.001	***
Children Present in Household	0.32	0.316	
Pets Present in Household	-0.29	0.468	
More than 10 Years Living in the County	-1.56	<0.001	***
Number of Observations	645		
ρ^2	.29		
$\bar{\rho}^2$	.25		
Initial Log-Likelihood	-447.1		

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

The model results were largely similar and consistent with those found in past literature on the choice to evacuate or not. Mandatory evacuation orders have been consistently found to increase likelihood to evacuate (Whitehead et al., 2000; Hasan et al., 2012; Murray-Tuite and Wolshon, 2013; Hasan et al., 2011; Xu et al., 2016; Yin et al, 2016; Wong et al., 2018). However, additional latent class analysis helps identify groups of people who are more likely to respond to these evacuation orders. Risk perceptions have also been found in literature to impact evacuation likelihood, indicating the accuracy of the LCCM (Whitehead et al., 2000; Zhang et al., 2004; Stein et al., 2010; Huang et al., 2012; Wong et al., 2018). While the exact description of these risk variables differs by study, literature has determined that increasing risk (perceived or real) increases evacuation likelihood. Barriers to evacuation choice, such as perceived housing costs and availability, work requirements, and gasoline availability, have been largely assessed in evacuation logistic research (see Lindell et al., 2019 for overview). Several studies found that work requirements decrease evacuation likelihood (Hasan et al., 2011; Hasan et al., 2012; Yin et., 2016), which mirrors our results. A higher number of individuals in the household and lower income, which can be tied to difficulties finding and paying for housing, were also found to decrease evacuation likelihood (Zhang et al., 2004; Smith and McCarty, 2009; Solis et al., 2010; Hasan et al., 2011; Hasan et al., 2012; Murray-Tuite et al., 2012). Solis et al. (2010) also found that higher evacuation planning costs were tied to a decreased evacuation likelihood, while Huang et al. (2012) determined that perceived evacuation impediments (i.e., property protection from looters and storm, evacuation expenses, traffic accidents) also decreased likelihood. One model improvement that advances prior work is that we identified the specific barriers and risks that impact choice in greater detail (i.e., housing cost, housing availability, and gas availability).

Focusing on demographic variables, we found that previous evacuees were less likely to be part of the evacuation-keen class, which confirms other literature that found previous hurricane experience lowered evacuation rates (Hasan et al., 2011; Hasan et al., 2012; Huang et al., 2012). We do mention that Solis et al. (2010) found hurricane experience to increase evacuation likelihood. Long-time residents have also been found to be less likely to evacuate (Zhang et al., 2004; Deka and Carnegie, 2010). We also found females to be less likely to evacuate, but this was not significant. Past research has found that females are more likely to evacuate (Riad et al., 1999; Whitehead et al., 2000; Smith and McCarty, 2009). The difference in our model could be attributed to a high proportion of females who are the primary household decision makers in our survey. We also retain insignificant indicators for children and pets in the household, which increase and decrease likelihood to evacuate, respectively. Prior research has found that families are more likely to evacuate (Smith and McCarty, 2009; Solis et al., 2010; Hasan et al., 2011; Hasan et al., 2012; Yin et al., 2016; Wong et al., 2018), while those with pets are less likely to evacuate (Whitehead et al., 2000; Solis et al., 2010; Yin et al., 2016). In all, we found similar results in our model compared to past literature, indicating that the LCCM is suitable for evacuation behavioral analysis. However, development of LCCMs across other disasters and datasets will be needed to assess the generalizability of the model.

Through this latent class construction, we produced additional understanding that a binary logit did not provide. We emphasize that prior research on the role of evacuation orders has only determined if evacuation orders impact evacuation choice to the overall population (binary logit) or a heterogeneous population (mixed logit). In our construction, we identified the specific people who are influenced by mandatory orders, which allows agencies to more closely target orders. Specifically, we learned whether a socio-demographic characteristic or risk perception was associated with receipt of a mandatory evacuation order, and we found heterogeneity existed for how individuals respond to mandatory evacuation orders. For example, previous evacuees who have shown a tendency to not evacuate may be persuaded to evacuate through a mandatory evacuation order. This signals to agencies that they should target outreach to areas evacuated from recent hurricanes to increase future evacuation rates. This additional behavioral insight and associated policy implication can be extended to other individuals who are more likely to be evacuation-reluctant to increase compliance.

4. Evacuations as a Multi-Dimensional Choice: Development and Application of a Portfolio Choice Model (PCM)

After deciding to evacuate, an individual is faced with a multi-dimensional choice composed of the concurrent decisions regarding departure day, departure time of day, destination, shelter type, mode, and route. These dimensions exhibit strong dependency as seen in the simple bivariate cross tabulations in Table 2. Moreover, literature has found correlation among these choices, indicating they should be jointly modeled (Fu and Wilmot, 2004; Fu et al., 2006; Gudishala and Wilmot, 2012; Bian, 2017; Gehlot et al., 2018, Wong et al., 2018). For example, we find that destination and departure timing are mutually dependent: far-away destinations require evacuees to leave earlier. To capture this and other dependencies without imposing any arbitrary hierarchy (e.g., since we do not know whether destination determines departure day timing, or vice versa, or both), we applied a PCM in an evacuation context.

Table 2. Visualization of a Series of Cross Tabulation Chi-Squared Results for Each Choice with Associated p-value and Categorization of Choices for Cross Tabulation

	Departure Day	**Departure Time of Day**	**Mode**	**Route**	**Destination**	**Shelter**
Departure Day						
Departure Time of Day	28.77 (0.001***)					
Mode	9.55 (0.975)	1.33 (0.995)				
Route	47.13 (<0.001***)	10.58 (0.227)	6.40 (0.983)			
Destination	107.56 (<0.001***)	19.26 (0.004**)	31.68 (0.002**)	150.64 (<0.001***)		
Shelter	26.71 (0.370)	7.35 (0.692)	20.45 (0.430)	56.07 (<0.001***)	77.77 (<0.001***)	

* 95% significance, ** 99% significance, *** 99.9% significance

Categories for Cross Tabulations
Note: Not identical to PCM categories

Departure Day
More than Three Days Before Landfall
Three Days Before Landfall
Two Days Before Landfall
One Day Before Landfall
Landfall Day and After

Departure Time
Nighttime (6:00 pm-5:59 am)
Daytime (6:00 am - 5:59 pm)

Transportation Mode
One Vehicle (i.e., automobile)
Two Vehicles or More (i.e., automobiles)
Shared Mode (i.e., bus, rail, aircraft, carpool)
Other Personal Mode (i.e., rental car, RV, walk, bicycle)

Majority Route Taken
Highways
Major Roads, Non-Highway
Local/Rural Roads
No Majority

Destination
Out of Florida
Within County
Within Florida, Out of County

Shelter Type
Friend's Residence
Family Member's Residence
Hotel/Motel
Public Shelter
Other (i.e., second residence, RV, Airbnb)

Framing choice alternatives as a portfolio that is composed of a bundle of choice dimensions, PCMs have been used predominantly to understand another multi-dimensional context: tourism behavior. In a vacation context, decision makers often concurrently consider their destination, trip duration, transportation mode, and accommodation type. While some work has used nested logit structures for tourism choice (Huybers, 2003), the bundling of choices into portfolios has led to intuitive and clear models for explaining tourism behavior (Dellaert et al., 1997; Grigolon et al., 2012; Van Cranenburgh et al., 2014a; Van Cranenburgh et al., 2014b). Tourism choice also exhibits clear parallels with evacuation choice. For example, in vacation choice, respondents have a joint dislike for flying and destinations closer to home, which can also be reached by train and car (Van Cranenburgh et al., 2014a). This intuitive result may hold as well for evacuation choice as there may be a joint preference for long-distance destinations and flying. More generally, we recognize that the PCM lends itself to the evacuation context, since it recognizes the multi-dimensionality and interdependency (between dimensions) of choice making.

We note that some joint modeling techniques, such as sequential logit models, require a specific ordering hierarchy chosen by the modeler. For the nested logit model, the modeler could either model all nests (which would require a large sample size to estimate all cross-elasticities) or limit interactions within nests to decrease the model complexity and data needs. A PCM is a theoretically compatible model for evacuation decision making and can easily capture correlation (if present) for a smaller sample size without imposing any hierarchy. Moreover, the PCM identifies correlations that could be further studied using sequential logit and nested logit models.

To begin, we constructed a series of portfolios composed of the primary dimensions an evacuee must consider: departure day; departure time; destination; shelter; mode; route. The core idea behind a PCM is that a choice is made between all possible combinations (called portfolios) of dimensions: each portfolio being a bundle of values, one per dimension. In a PCM, each possible combination of values (one per dimension such as a particular departure day in combination with a particular destination and a particular transport mode, and so forth) constitutes an alternative that may be chosen by an individual. All alternatives together constitute the portfolio choice set. The utility of each portfolio consists of a part-worth utility associated with the portfolio's value or score on each particular dimension (e.g., a part-worth utility for a within county destination), plus the additional utilities that are associated with interactions between the different dimensions (e.g., a penalty for the combination of early departure and within county destination). To these utility terms, socio-demographic interaction terms may also be added. Finally, an error term is added to represent heterogeneity in utilities across individuals. Depending on the distribution of this error term, various specifications can be obtained for the choice probabilities of each alternative (portfolio). In our paper, as is usual in the PCM literature, we assume i.i.d. EV Type I errors, leading to closed form logit probabilities. Based on observed choices, parameters can be estimated for the different dimensions and their interactions (as well as for interactions with socio-economic variables). The result is a model that captures the jointness of the decision and the interdependencies between the multiple dimensions of the decision, without imposing sequencing or order in those dimensions.

We recognize that we need to determine a suitable level of granularity for the dimensions. High granularity (more categories per dimension) leads to very large choice sets (up to a maximum of 5*2*4*4*3*5=2,400 portfolios per choice set in our case, see Table 2) and risks offering a false sense of precision in light of possible measurement errors present in the data. Based on pre-testing, we split each dimension into a suitable number of categories to offer a rich overview of behavior that is policy applicable. Subsequently, we constructed 144 portfolios (Table 3) by categorizing the different dimensions as follows:

- Departure Day: Early, Regular, Late
- Departure Time of Day: Night, Day
- Destination: Within County, Out of County but Within Florida, Outside Florida
- Shelter: Private, Public
- Mode: Two or More Vehicles, One Vehicle or Other
- Route: Highway, Non-Highway

For example, a possible portfolio (i.e., choice alternative) could be 'Early, Day, Within County, Private, 1 Vehicle, and Highway.' Not every portfolio in the portfolio choice set is chosen at least once. Note that this does not pose any problem with regards to econometric identifiability of parameters. To see this, note that the choice dimensions in a portfolio model are analogous to the attributes (e.g. time and cost) of alternatives (e.g. routes) in a conventional choice model; parameters for these attributes can of course still be estimated even if a choice for a particular combination of attribute values (e.g. a particular combination of travel time and cost) is absent in the dataset. Likewise, in the context of a PCM, parameters can be estimated for each dimension and for interactions between dimensions, even when combinations of dimension-values are not observed. We estimated the PCM using a maximum likelihood estimator employing the Python package *Pylogit* (Brathwaite and Walker, 2018).

Table 3. Consolidation of Choices for the Portfolio Choice Model

Choices Considered	***Percentage of Evacuees***	***Shorthand***
Departure Date		
Early Evacuees (More than three before)	20.1%	Early
Regular Evacuees (Two to three days before)	54.6%	Regular
All Other Evacuees (One day or less before)	25.3%	Late
Departure Timing by Hour		
Night (6:00 p.m. – 5:59 a.m.)	32.8%	Night
Day (6:00 a.m. – 5:50 p.m.)	67.2%	Day
Destination Choice		
Evacuated inside same county as residence	17.1%	Within County
Evacuated to a different county in Florida	34.3%	Within Florida
Evacuated out of Florida	48.6%	Out of Florida
Mode Choice		
Two or more personal vehicles	24.2%	2+ Vehicles
One personal vehicle and all other modes	75.8%	One Vehicle/Other
Shelter Type		
Private Shelter (Friends/Family/Other)	69.1%	Private
Public Shelter (Local Shelter/Hotel/Motel)	30.9%	Public
Primary Route by Road Type		
Highways	64.1%	Highway
Major/Local/Rural/No Majority Type	35.9%	Non-Highway

Total Portfolios: 144
Chosen Portfolios: 91

4.1 PCM Primary Variables

When we modeled the dimensions constructing the PCM (not allowing for interdependencies between dimensions), nearly all dimensions were significant and corresponded to the survey results (Table 4). Individuals were less likely to prefer evacuating early (without joint influence from other variables), but they were more likely to prefer evacuating during a regular time (2-3 days before landfall) in contrast to late evacuees (one day or less before landfall). Evacuees were less likely to choose a night evacuation over a daytime evacuation. They also preferred to leave the state of Florida in contrast to evacuating within the county or into another county in Florida. Evacuees preferred private to public shelters, and highway routes were more likely to be chosen over non-highway routes. Individuals were also less likely to evacuate with two or more vehicles.

4.2 PCM Primary Variables + Interactions

To build a more insightful model with more explanatory power, we considered the impact of primary variable interactions. With the addition of interaction effects, variables for regular time evacuees and highway evacuees became insignificant, while the early evacuee variable became significant. Some primary variables also changed signs, indicating that the inclusion of interaction effects revealed different (more nuanced) insights and predictions. Ultimately, the key benefit of the variable interactions was to identify a joint preference for or against a combination of primary variables. We found that the inclusion of variable interaction effects doubled the model fit.

Results indicated that evacuees have a joint preference for evacuating early, at night, and on highways. This should be interpreted as follows: the probability that a randomly sampled individual will, for example, evacuate early and at night is higher than what would be predicted based on the two direct effects of these variables. The same holds for early departure and choosing highways. During early days of the evacuation, evacuees did not face visibility risks at night due to the hurricane, and the highways were largely clear of congestion. We found the same joint preferences for regular time evacuees when interacted with both night and highway variables. We found, however, that there is a joint disutility for evacuating early and within Florida along with evacuating early and within county, largely because these destinations were physically closer than out-of-state destinations. We found a joint preference against evacuating at night and evacuating within Florida and within the county. Given the shorter travel distances, evacuees did not need to evacuate at night to avoid congestion. However, night evacuations and private shelter types had a positive interaction. This may be because friends and family were flexible in accepting evacuees during all hours of the day. Several additional interactions were found to be significant for within county evacuations including a joint preference for two or more vehicles but a joint preference against highways. Evacuees only traveling short distances may have felt more comfortable taking multiple vehicles and would be less likely to route on highways given their knowledge of local roads. We found a similar result for individuals who evacuated to a different county in Florida. Within Florida but out-of-county evacuations also negatively interacted with private shelters. This may be indicative of the predominance of public shelters throughout Florida.

4.3 PCM: Primary Variables + Interactions + Demographics

While the inclusion of secondary interactions begins to form clearer policy connections, adding demographics adds further insight and explanatory power to determine the groups of people who prefer specific dimensions of the evacuation choice. We find that the fit improves to 0.166, triple the fit of the original model. We visualize how each additional variable changes the total utility of an early evacuation for an individual with all the same characteristics in Figure 1. Evacuees from Southeast and Southwest Florida and who have lived in their current residence for less than one year were more likely to be early evacuees. Those geographic areas of Florida received warnings and mandatory orders first. People with little experience in their current residence may be unsure if their structure would be able to withstand the hurricane and may not have implemented hurricane-specific home improvements. Households with children were more likely to be both early and regular time evacuees. Families may have a stronger risk aversion, leading them to evacuate early.

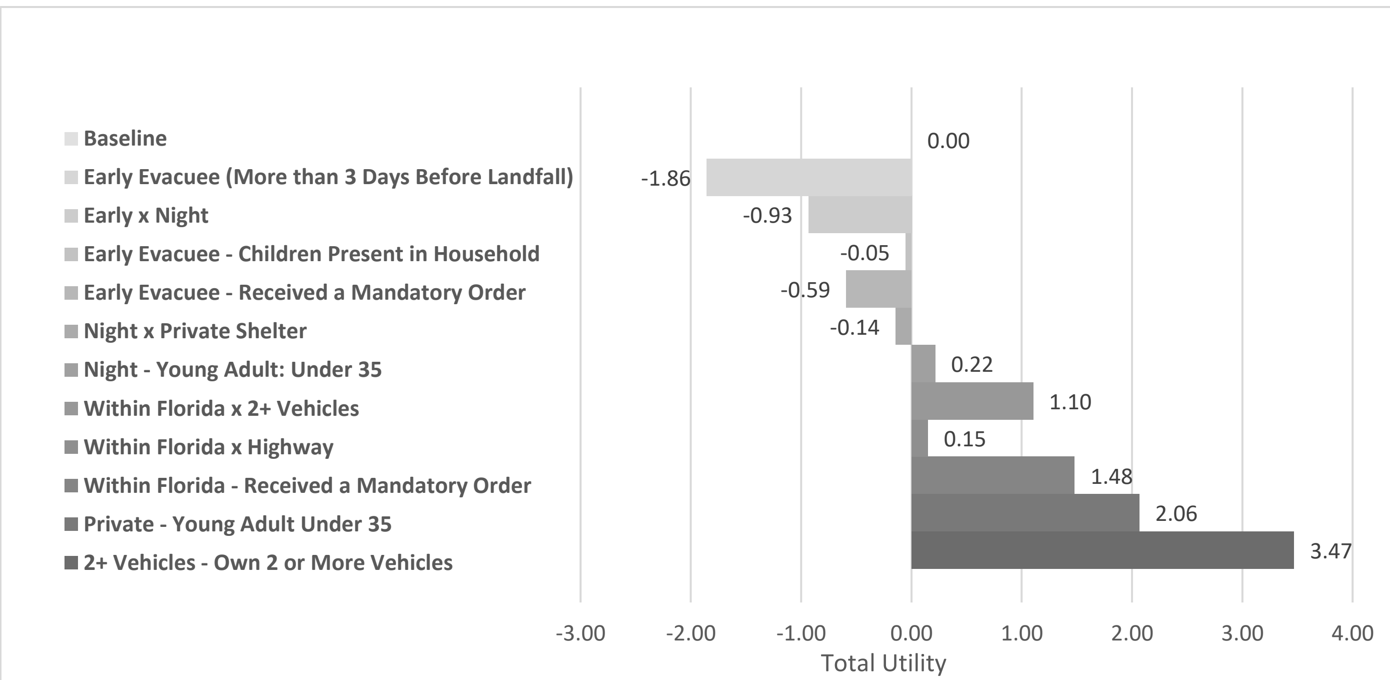

Figure 1. Visualization of the decomposed total utility of evacuating early, at night, to a private shelter within Florida, with two vehicles using the highway, for an individual who has children present in the household, is under 35 years of age, owns two or more vehicles, and received a mandatory order to evacuate. Note: total utility equals 3.47. Bars show how this total is a function of the utilities associated with primary variables and interactions.

Individuals with extreme worry about traffic congestion were more likely to evacuate at night. This is unsurprising considering the majority of congestion occurs during the day. Long-time residents (i.e., over 10 years in residence) and previous evacuees were also more likely to evacuate at night. With prior hurricane experience and knowledge of local routes, these individuals may have felt comfortable evacuating at night. Young adults (under 35) were also more likely to evacuate at night, possibly because they have more comfort driving under low-visibility conditions. However, those who were extremely worried about finding gas were less likely to evacuate at night. The majority of gasoline resupplies to gas stations occurred during the morning hours, and evacuees may have worried about finding empty stations during their evacuation.

Table 4 Portfolio Choice Model Results

	Primary			Primary + Interactions			Primary + Interactions + Demographics		
	Est. Coef.	**p-value**		**Est. Coef.**	**p-value**		**Est. Coef.**	**p-value**	
Primary Variables									
Early Evacuee (More than Three Days Before Landfall)	-0.15	0.348		-0.71	0.050	*	-1.86	<0.001	***
Regular Time Evacuee (Between 2-3 Days Before Landfall)	0.64	<0.001	***	-0.29	0.153		-0.40	0.155	
Night Evacuee (Between 6:00 pm and 5:59 am)	-0.53	<0.001	***	-1.14	0.002	**	-1.89	<0.001	***
Within County Evacuee (Destination Within County)	-0.41	0.007	**	1.59	<0.001	***	-0.73	0.547	
Within Florida Evacuee (Destination to Other County)	-0.32	0.006	**	2.02	<0.001	***	0.76	0.297	
Private Shelter Evacuee (Friend's or Family's Residence)	0.66	<0.001	***	0.84	<0.001	***	0.20	0.536	
2+ Vehicle Evacuee (Used Two or More Vehicles)	-0.84	<0.001	***	-1.50	<0.001	***	-2.29	<0.001	***
Highway Evacuee (Used Highway for Majority of Route)	0.56	<0.001	***	0.33	0.250		0.61	0.052	
Interactions									
Early x Night	-----	-------	----	0.96	0.012	*	0.92	0.016	*
Early x Within Florida	-----	-------	----	-0.80	0.013	*	-0.95	0.004	**
Early x Highway	-----	-------	----	1.03	0.007	**	1.07	0.005	**
Regular x Night	-----	-------	----	0.51	0.107		0.53	0.098	
Regular x Highway	-----	-------	----	1.39	<0.001	***	1.38	<0.001	***
Night x Within Florida	-----	-------	----	-0.65	0.015	*	-0.57	0.035	*
Night x Private Shelter	-----	-------	----	0.51	0.050	*	0.45	0.088	
Within County x Early	-----	-------	----	-1.10	0.158		-1.12	0.154	
Within County x Night	-----	-------	----	-0.73	0.055		-0.66	0.084	
Within County x 2+ Vehicles	-----	-------	----	1.06	0.002	**	1.12	0.001	***
Within County x Highway	-----	-------	----	-2.29	<0.001	***	-2.29	<0.001	***
Within Florida x Private Shelter	-----	-------	----	-0.86	<0.001	***	-0.86	<0.001	***
Within Florida x 2+ Vehicles	-----	-------	----	0.88	0.002	**	0.89	0.002	**
Within Florida x Highway	-----	-------	----	-0.95	0.001	***	-0.95	0.001	***
Variables for Early (Base: Late)									
Living in Southeast Region of Florida	-----	-------	----	-----	-------	----	3.87	<0.001	***
Less than One Year in Current Residence	-----	-------	----	-----	-------	----	1.48	0.001	***
Children Present in Household	-----	-------	----	-----	-------	----	0.88	0.010	**

Living in Southwest Region of Florida	-----	-------	----	-----	-------	----	0.63	0.084	
Received a Mandatory Order	-----	-------	----	-----	-------	----	-0.54	0.078	
Variables for Regular (Base: Late)									
Living in Southeast Region of Florida	-----	-------	----	-----	-------	----	2.27	0.030	*
Less than One Year in Current Residence	-----	-------	----	-----	-------	----	0.92	0.017	*
Children Present in Household	-----	-------	----	-----	-------	----	0.48	0.073	
Living in Southwest Region of Florida	-----	-------	----	-----	-------	----	-0.84	0.002	**
Variables for Night (Base: Day)									
Extreme Worry of Traffic	-----	-------	----	-----	-------	----	0.72	0.006	**
More than 10 Years in Residence	-----	-------	----	-----	-------	----	0.65	0.049	*
Received a Voluntary Order	-----	-------	----	-----	-------	----	0.64	0.008	**
Previous Evacuee	-----	-------	----	-----	-------	----	0.42	0.086	
Young Adult: Under 35	-----	-------	----	-----	-------	----	0.36	0.164	
Extreme Worry of Finding Gas	-----	-------	----	-----	-------	----	-0.54	0.047	
Variables for Within County (Base: Out of Florida)									
Living in the Southeast Region of Florida	-----	-------	----	-----	-------	----	2.12	0.005	**
Experienced a Hurricane Before	-----	-------	----	-----	-------	----	1.87	0.099	
Received a Mandatory Order	-----	-------	----	-----	-------	----	1.07	0.001	***
Living in the Central West Region of Florida	-----	-------	----	-----	-------	----	0.83	0.196	
Household Income $100,000 and Over	-----	-------	----	-----	-------	----	-1.02	0.010	**
Variables for Within Florida (Base: Out of Florida)									
Received a Mandatory Order	-----	-------	----	-----	-------	----	1.33	<0.001	***
Living in the Southeast Region of Florida	-----	-------	----	-----	-------	----	1.28	0.003	**
Living in the Central West Region of Florida	-----	-------	----	-----	-------	----	1.13	0.151	
Experienced a Hurricane Before	-----	-------	----	-----	-------	----	0.77	0.198	
Extreme or Some Likelihood Belief of Injury/Death	-----	-------	----	-----	-------	----	-0.67	0.006	**
Household Income Under $40,000	-----	-------	----	-----	-------	----	-0.70	0.052	
Variables for Private Shelter (Base: Public Shelter)									
Extreme Worry of Severity of Irma	-----	-------	----	-----	-------	----	0.71	0.004	**
Pet(s) Present in Household	-----	-------	----	-----	-------	----	0.68	0.013	*
Young Adult: Under 35	-----	-------	----	-----	-------	----	0.59	0.033	*
Extreme or Some Worry of Finding Housing	-----	-------	----	-----	-------	----	-0.71	0.008	**
Extreme Worry of Housing Cost	-----	-------	----	-----	-------	----	-1.01	0.002	**
Variables for 2+ Vehicles (Base: One Vehicle/Other)									
Own Two or More Vehicles	-----	-------	----	-----	-------	----	1.40	0.001	***
One and Two Person Households	-----	-------	----	-----	-------	----	-0.53	0.058	
Less than One Year in Current Residence	-----	-------	----	-----	-------	----	-0.90	0.021	*
Variables for Highway (Base: Non-Highway)									
Extreme Worry of Finding Gas	-----	-------	----	-----	-------	----	-0.54	0.016	*
Number of Observations	368			368			368		
ρ^2	0.053			0.093			0.166		
$\bar{\rho}^2$	0.048			0.079			0.131		
Final Log-Likelihood	-1,573			-1,506			-1386		

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

For destination choice, evacuees from the Southeast and Central-West regions of Florida were more likely to evacuate within county or out-of-county but within Florida. We found the same result for those who received a mandatory evacuation order. It is not immediately clear why these individuals stayed closer versus traveling out-of-state. One possibility is that these orders contained additional information about shelters nearby and encouraged evacuees to remain close. Another possibility is these residents may have wanted to remain close to inspect damage. Interestingly, belief of injury/death was only significant for out-of-county, but within Florida, evacuees. Evacuees who stayed closer within county may have been willing to accept the risks in favor of other benefits (easier communication streams, quicker access back to residence). Wealthy households were less likely to evacuate within county, likely due to having access to more assets/resources to travel further distances.

For sheltering choice, individuals who had extreme worry regarding Irma severity were more likely to seek a private shelter, possibly to be closer to their social connections. Households with pets were more likely to evacuate to private shelters, which were more likely to accept pets in contrast to public shelters. Young adults (under 35) were also more likely to evacuate to a private shelter, which may be related to their stronger friend networks. Those worried about finding housing and housing costs were less likely to evacuate to a private shelter. These worries may have been related to a limited network to assist in sheltering, adding new evacuation logistic challenges that must be overcome.

Evacuees owning two or more vehicles were more likely to use two or more vehicles while evacuating. Alternatively, smaller households with fewer drivers and vehicles were less likely to use two or more vehicles. Regarding highway evacuations, those with extreme worry of finding gas were less likely to use highways. Evacuees may have perceived congestion and gas shortages to be linked and were willing to use smaller roads to find stations. Overall, we did not find any other significant variable for highway evacuations, suggesting that the choice may be more related to the variables of the route and less on demographic variables.

4.4 Overall PCM Observations and Limitations

With each successive addition of independent variables and interactions in the PCMs, we found new insights and increased explanatory power. While we recognize that the final model contains a high number of parameters for the dataset size, we found strong behavioral consistency and significant variables. We retained most variables with a p-value under 0.20 as these mostly significant factors were often tied to important policy implications. While this modeling choice does increase the number of variables in the model, we found that the adjusted fit of the model – which penalizes additional variables – is still close to the overall fit. Moreover, the inclusion of demographic variables led to significance changes in the primary dimensions, suggesting strong explanatory power of demographics and the need for these additional variables.

We recognize that a larger sample size of evacuees and samples across different disasters may be necessary to determine the internal validity of the model, the model's generalizability, and if the number of variables is appropriate. For generalizability, wildfire evacuees face different evacuation circumstances, particularly related to evacuation orders, departure timing, and route choice. However, the strong results, particularly related to the correlation among choices, indicates that PCMs can play a role in identifying evacuee behavior. Moreover, the assumption-poor nature of PCMs identifies correlated choices that could be modeled sequentially or jointly using other assumption-strong discrete choice models. We find that PCM estimates joint correlation between within county evacuations and departure times, which justifies the claim made in Gehlot et al. (2018) for a joint model of evacuation departure and travel times.

In addition, the PCMs may be extended to consider different levels of granularity (or additional categories) for each choice. Theoretically, the model could be calibrated for specific policy needs for agencies, one of the model's strongest assets. The PCM can also be expanded to consider unobserved heterogeneity between decision makers using a mixed logit structure. We tested this extension but found no significant improvement in fit, most likely because we only have one observation per individual in the revealed preference setting, which hampers the identification of standard deviations of randomized parameters.

We also note that several other variables could significantly impact choices in the PCM, particularly variables associated with the situational conditions of the hurricane (i.e., current weather conditions, predicted storm surge) or the evacuation (i.e., road conditions, traffic levels, traffic control response measures). During data collection, we did not ask respondents about these situational conditions – perceived or actual. This is a limitation that should not only be addressed for further exploration of the PCM but also other behavioral models of evacuation choice. We recommend that future revealed preference surveys measure the perceived situational conditions or infer the actual conditions based on weather reports, traffic data, departure timing, route choice, and destination choice.

Another key limitation is that we did not ask respondents about their mobilization time (i.e., the time it takes for a household to prepare to evacuate). Intuitively, this mobilization time should impact departure timing and possibly destination choice and route choice, if conditions change during preparation. Some work, such as Sadri et al. (2013) modeled mobilization time using a mixed probit model, finding that the source and timing of evacuation orders, work requirements, and demographic variables (i.e., previous evacuee, income, race) influenced mobilization time. Most importantly, the work found that mobilization time and shelter choice were tied: those evacuating to public shelters were more likely to mobilize quickly, perhaps since shelters provide critical survival supplies (Sadri et al., 2013). We recognize that future work on the PCM model could incorporate this mobilization time dimension, if this information is known.

Finally, we acknowledge that we did not consider the role of social networks in the evacuation choices in the PCM. We would expect that peer influences, whether from closer relationships or neighbors, would influence some evacuation choices. For example, stronger networks would be expected to increase likelihood to shelter with friends and family. However, we did not collect information on the influence of peers or social networks in our survey. This oversight should be corrected in future revealed preference surveys, taking cues from recent studies on social networks, including joint decision making between evacuees (Sadri et al., 2017a; Sadri et al., 2017b).

5. Conclusions

The study of evacuation behavior, despite major advances in recent years, still has a number of critical opportunities and gaps: 1) possibility of obtaining new behavioral insights from latent class choice models for evacuee behavior; and 2) lack of multi-dimensional choice modeling despite clear dependency among concurrent evacuation decisions.

Using revealed preference data of individuals impacted by Hurricane Irma, we addressed the first gap by developing an LCCM that adds behavioral insights through two distinct classes of individuals. We found two clear classes exist: 1) a class of keen evacuees who were driven to evacuate through risk perception and 2) a class of reluctant evacuees who preferred to stay in part due to a perception of significant evacuation logistic barriers yet could be encouraged to leave by receiving a mandatory evacuation order. This additional information, connected to class membership, pinpoints who should be targeted with a mandatory evacuation order. To increase compliance rates, agencies should consider:

- Focusing orders on previously evacuated hurricane zones and neighborhoods with long-time residents;
- Strengthening order language to convey disaster risk;
- Increasing public shelters and alternative shelter availability to reduce concerns over finding and paying for housing; and
- Conveying sheltering information, including shelters that accept pets, concurrently with mandatory orders.

To address the second gap, we constructed three PCMs with increasing complexity that could jointly model the multi-dimensional choice for evacuees. We found that multiple individual and household variables, risk perception variables, and dimension variables were significant. We also discovered that evacuees have a joint preference or joint dislike for certain secondary interactions among the concurrent decisions, further indicating choice dependency. Most importantly, we showed the applicability of the PCM in the evacuation field by successfully modeling multiple dimensions jointly without an imposed hierarchical structure. The results from the model, especially the interacted dimensions, indicate several policy recommendations for agencies to improve hurricane evacuations. These include:

- Ensuring agency resources to manage significant nighttime traffic along highways well before hurricane landfall;
- Preparing for significant long-distance nighttime traffic through interstate communication and resource placement;
- Deploying traffic management resources locally to handle significant multiple-vehicle evacuations; and
- Setting resources for traffic and public shelters for medium- and short-distance evacuees at least three days before landfall.

While the PCM requires additional verification using other revealed preference datasets to increase its internal validity and generalizability, this research signifies a key step toward more accurately analyzing evacuation behavior using discrete choice theory with direct policy implications.

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9. APPENDIX

9.1 Latent Class Choice Model Methodology

Following the methodology provided in El Zarwi *et al*. (2018), we first consider a class-specific model for the decision to evacuate or not. We are interested to know the probability that an individual n makes a choice y_{ni} to evacuate or not (where $i = 1$ is evacuate and $i = 0$ is not evacuate). This probability is conditional on the decision maker belonging to latent class s.

Assuming the decision maker maximizes his utility and that part of that utility is unobserved by the analyst, we formulate the utility of evacuating or not which is associated with individual n, conditional on the individual belonging to latent class s as:

$$U_{ni|s} = V_{ni|s} + \varepsilon_{ni|s} \qquad (1)$$

where $V_{ni|s}$ is the systematic utility, which in our case consists of the sum of an intercept (i.e., a constant) and the product of the dummy variable 'received a mandatory order' and its associated parameter; note that this latter parameter and the intercept are class-specific. Errors $\varepsilon_{ni|s}$ are white noise disturbances, which are assumed to be independently drawn from an Extreme Value Type 1 distribution with a variance of $\pi^2/6$. After normalizing the systematic utility of not evacuating to 0, we may express the class-specific probability to evacuate as follows:

$$P(y_{n1}|s) = P\left(U_{n1|s} \geq U_{n0|s}\right) = \frac{\exp\left(V_{n1|s}\right)}{1+\exp\left(V_{n1|s}\right)} \qquad (2)$$

Ours is a two-class model. We denote the probability that an individual belongs to the first class by $P(q_{n1}|Z_n)$ where Z_n are the characteristics of the decision maker and the decision context faced by him. Vector γ contains coefficients associated with each of these characteristics. Assuming the same error distribution as before, we can express this probability as:

$$P(q_{n1}|Z_n) = \frac{\exp\left(\gamma' Z_n\right)}{1+\exp\left(\gamma' Z_n\right)} \qquad (3)$$

Equations 2 and 3 are combined to find the marginal probability, which is the probability that a randomly sampled individual n will evacuate, as:

$$P(y_{n1}) = P(y_{n1}|q_{n1}) \cdot P(q_{n1}|Z_n) + P(y_{n1}|q_{n2}) \cdot \left(1 - P(q_{n1}|Z_n)\right) \tag{4}$$

9.2 Appendix Tables

Table A1. Household and Individual Respondent Demographics

County of Residence	
Brevard	53.2%
Lee	17.2%
Collier	13.3%
Miami-Dade	3.7%
Pinellas	2.9%
Monroe	2.6%
Broward	2.5%
All other counties	4.5%
Distance from Major Water Source	
Next to Major Source	15.3%
1 mile	16.4%
2 to 4 miles	20.7%
5 to 9 miles	23.6%
10 to 20 miles	17.8%
Over 20 miles	3.6%
No answer	2.6%
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%
Length of Current Residence	
Less than 6 months	9.5%
6 to 11 months	7.9%
1 to 2 years	22.6%
87.3 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%

Gender	
Female	81.9%
Male	18.1%
Age	
18-24	3.1%
25-34	26.0%
35-44	28.7%
45-54	21.7%
55-65	14.9%
65+	5.6%
Race	
White	94.0%
Black or African-American	1.6%
Mixed	1.1%
Asian	0.9%
Native American/Alaska Native	0.2%
Pacific Islander	0.2%
No answer/Prefer no answer	2.2%
Ethnicity	
Not Hispanic	89.5%
Hispanic	6.7%
No/prefer no answer	3.9%
Education	
High school graduate	6.5%
Some college	18.6%
Two-year degree	12.9%
Four-year degree	32.1%
Professional degree	26.4%
Doctorate	3.6%
Employment	
Employed full time	65.7%
Employed part time	10.2%
Unemployed	9.6%
Retired	8.7%
Disabled	2.3%
Student	2.2%
No answer/Prefer no answer	1.2%

Household Characteristics	
Household with Disabled	16.4%
Household with Children	44.8%
Household with Elderly	15.0%
Households with Pets	77.1%
Household Income	
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%
$150,000 or More	12.4%
No/prefer no answer	11.8%
Primary Transportation Mode	
Drive alone using automobile	94.3%
Work from home	1.7%
Carpool/vanpool	0.9%
Bus	0.8%
Bicycle	0.6%
Walk	0.3%
Motorcycle/scooter	0.3%
Shared mobility	0.2%
Other	0.9%
Mobile Phone Type	
Own a smartphone	96.3%
Own a non-smartphone	3.4%
Do not own a cell phone	0.3%
Access to Internet at Home	
Yes	98.3%
No	1.7%
In-Vehicle/Smartphone Navigation	
Yes	87.9%
No	12.1%

*Federal Emergency Management Agency

Table A2. Cross Tabulation of Evacuation Decision and Receiving a Mandatory Evacuation Order

		Evacuated		
		Yes	No	Total
Received a Mandatory Order	Yes	69.5%	**30.5%** *(Non-Compliance Rate)*	46.2% (n = 298)
	No	**46.4%** *(Shadow Evacuation Rate)*	53.6%	53.8% (n = 347
	Total	57.1% *(n = 368)*	42.9% *(n = 277)*	n = 645

Table A3. Descriptive Results of Key Evacuation Choices (n = 368)

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%
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%
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%
Destination by State	
Florida	51.4%
Georgia	12.0%
Tennessee	6.8%
North Carolina	5.7%
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%
Usage of GPS for Routing	
Yes, and followed route	63.6%
Yes, but rarely followed route	6.5%
No	29.9%
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%
Multiple Destinations	
Yes	28.0%
No	72.0%
Reentry Date	

Alabama	4.9%	*Before Sunday, Sept. 10	10.9%
South Carolina	3.5%	Sunday, Sept. 10	1.6%
Virginia	2.4%	Monday, Sept. 11	18.5%
Louisiana	1.6%	Tuesday, Sept. 12	22.0%
Mississippi	1.6%	Wednesday, Sept. 13	12.5%
Ohio	1.6%	Thursday, Sept. 14	8.2%
Pennsylvania	1.6%	Friday, Sept. 15	5.4%
All other states (under 5 respondents)	6.8%	Saturday, Sept. 16	4.1%
		Sunday, Sept. 17	7.1%
		After Sunday, Sept. 17	9.8%

Note: Rounding may cause choices to not exactly equal 100%

Table A4. Binary Logit Model of the Decision to Evacuate or Not

Variable	Estm. Coef.	p-value	
Constant Evacuate	1.28	0.205	
Evacuation Experience			
Received a Mandatory Order	0.52	0.012	*
Concerns and Worry			
Extreme or Somewhat Likelihood Belief of Injury/Death	1.30	<0.001	***
Extreme Likelihood Belief of Major Structural Damage	1.21	<0.001	***
Extreme Worry of the Severity of Irma	0.91	<0.001	***
Extreme or Somewhat Worry of Finding Gas	-0.30	0.197	
Extreme or Somewhat Worry of Housing Cost	-0.63	0.012	*
Extreme Likelihood Belief of Work Requirements	-0.66	0.012	*
Extreme Worry of Finding Housing	-0.71	0.016	*
Individual Characteristics			
Race: White	0.19	0.676	
Female	-0.12	0.656	
Elderly: Age 65 and Over	-0.34	0.466	
Experienced a Hurricane Before	-1.16	0.138	
Previous Evacuee	-1.05	<0.001	***
Household Characteristics			
Mobile Home [Base: Site Build - House]	1.30	0.047	*
Site Build - Apartment [Base: Site Build - House]	1.02	<0.001	***
Children Present in Household	0.85	0.014	*
Less than One Year in Residence	0.51	0.071	
Central West Region [Base: Southwest]	0.48	0.462	
One or Two Person Household	0.37	0.289	
Pets Present in Household	-0.10	0.690	
Southeast Region [Base: Southwest]	-0.49	0.203	
Household Income Under $20,000	-0.67	0.171	
Northeast/Central-East Region [Base: Southwest]	-1.51	<0.001	***
Number of Observations	645		
ρ^2	0.31		
$\bar{\rho}^2$	0.26		
Final Log-Likelihood	-307.4		
Initial Log-Likelihood	-447.1		

* 95% significance
** 99% significance
*** 99.9% significance