Title
Compliance, Congestion, and Social Equity: Tackling Critical Evacuation Challenges through the Sharing Economy, Joint Choice Modeling, and Regret Minimization

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By

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Professor Mark Hansen

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Abstract

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By

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Emphasis in Transportation Engineering

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Evacuations are a primary transportation strategy to protect populations from natural and human-made disasters. Recent evacuations, particularly from hurricanes and wildfires, have exposed three critical evacuation challenges: 1) persistent evacuation non-compliance to mandatory evacuation orders; 2) poor transportation response, leading to heavy congestion, slow evacuation clearance times, and high evacuee risk; and 3) minimal attention in ensuring all populations, especially those most vulnerable, have transportation and shelter. With ongoing climate change and increasing land development and population growth in high-risk areas, these evacuation challenges will only grow in size, frequency, and complexity, further straining transportation response in disaster situations.

<u>Research Objectives and Theoretical and Methodological Contributions</u>: To tackle these three challenges and improve evacuation outcomes, I explored three research areas: the sharing economy, (joint) choice modeling, and regret minimization.

1) Sharing Economy: The sharing economy has grown rapidly in the past two decades, opening new mechanisms to share, sell, and buy goods and services via technology. Similar to other economic forms, the sharing economy must contend with and respond to external shocks, including disasters. Within this response, an opportunity arises: the sharing economy through private companies or residents could theoretically be a mechanism to increase available assets in evacuations and disasters. Due to the recent development of the sharing economy, research has yet to explore and assess this strategy fully. With limited evacuation literature in this area, an initial question arises: To date, what has been the role of the sharing economy in disasters? In addition, what are the benefits and limitations, particularly for vulnerable groups? On the private resident side, are people willing to share mobility and sheltering resources, and what influences this willingness? To address these questions and explore this new strategy, I tested the feasibility of the sharing economy by assessing the:

- Current state of the sharing economy in evacuations, benefits and limitations of the sharing economy in disasters, and the willingness of individuals to provide shared resources through archival research, expert interviews, and post-disaster surveys;
- Effect of different factors, including trust and compassion, on willingness to share transportation and sheltering through simple discrete choice models;
- Extent to which sharing economy platforms and shared resources can benefit or limit social equity for vulnerable populations through focus groups and application of the STEPS (spatial, temporal, economic, physiological, social) equity framework; and
- Behavioral nuances of different models – binary logit models, multi-choice latent class choice model, and portfolio choice model – for the willingness of individuals to share resources in multiple evacuation scenarios for transportation and sheltering.

2) (Joint) Choice Modeling: Disasters are stressful and complex events in which individuals must make rare choices related to evacuations and their safety. First, individuals must decide to evacuate or stay, after which evacuees must navigate through multiple complicated choices including departure day, departure time of day, transportation mode, destination, shelter type, route, and reentry time. Current evacuation behavior literature, while reflecting significant strides in recent years, contains several severe gaps. Much literature is focused on whether to evacuate or stay, with limited research on the complex decisions that must follow this initial choice. In addition, research has only minimally explored the different behavioral responses of unobserved classes of people or the influence of attributes of alternatives on choice. Choice modeling has also focused primarily on hurricanes, leaving a wide gap in the evacuation literature on wildfire behavior. What influences choice making in evacuations, particularly choices beyond the decision to evacuate or stay and especially for wildfire evacuations? Do attributes of alternatives or unobserved classes add behavioral understanding? Most importantly, literature has not considered the theoretical possibility that evacuation choices are inherently joint and multi-dimensional. What choices are correlated and dimensionally dependent, and how should this be modeled? I addressed these research gaps by applying a series of discrete choice models that conduct:

- An attribute-based assessment of wildfire evacuation choices beyond the decision to evacuate or stay through simple multinomial logit models;
- A latent classification of individuals for the decision to evacuate or stay via a latent class choice model for hurricanes; and
- An assessment of decision-dimensional dependency of hurricane choices and wildfire choices (departure day, departure time of day, destination, shelter type, transportation mode, and route) using a portfolio choice model.

3) Regret Minimization: Due to the risky and rare context of evacuations, people likely make decisions differently than under normal circumstances. Regret has been found to influence choices that are difficult and when individuals receive rapid feedback on whether their choices had positive or negative outcomes. Given the unique characteristics of disasters and evacuations, regret minimization (i.e., choice making by minimizing future anticipated regret) could theoretically present a more valid decision rule in evacuations than utility maximization, which has been assumed for most evacuation choice models. Literature in this area is limited, with few studies testing regret minimization in evacuations and only in a stated preference setting. Does random regret minimization (RRM) better describe evacuation behavior than traditional random utility maximization (RUM) in choice models? With no empirical testing of this theory in the literature using post-disaster data, what methodology should be used in a revealed preference setting to reconstruct complex evacuation choice sets and test regret minimization? To answer these research questions and test the theory of regret in evacuations, I analyzed:

- Regret minimizing behavior of wildfire evacuees by developing a revealed preference (RP) methodology for challenging choice sets.

Empirical Contributions: One primary challenge in the evacuation field is the collection of post-disaster data, which can be difficult for a variety of reasons related to finding participants, securing funding, not interfering with recovery efforts, and deploying data-gathering instruments quickly. Finding enough participants for data collection is especially difficult for wildfire evacuations (compared to hurricane evacuations), due to their smaller size. To meet these challenges and contribute data to the broader evacuation field, I distributed online surveys, collecting responses from individuals impacted by three disasters:

- 2017 Hurricane Irma in Florida: n=645 (collected Oct. - Dec. 2017);
- 2017 December Southern California Wildfires: n=226 (collected Apr. - June 2019); and
- 2018 Carr Wildfire: n= 284 (collected Feb. - Apr. 2019).

One critical limitation of online (and disaster) surveys is the failure to represent vulnerable populations. Consequently, I supplemented the wildfire surveys with a series of four focus groups composed of individuals from four vulnerable groups – low-income individuals, older adult, individuals with disabilities, Spanish-speaking individuals – each impacted by a California wildfire between 2017 and 2018 (collected Aug. 2018 - Apr. 2019). To establish a foundation for my research on the sharing economy, I also interviewed 24 high-ranking experts on the benefits and limitations of this strategy in disasters (collected Feb. 2017 - Apr. 2017).

Sharing Economy Results: I find several key limitations of the sharing economy for both private companies and private citizens in hurricanes and wildfires including concerns related to safety, social equity, communication, and driver reliability (Chap. 3, Chap. 5). Yet, the sharing economy could provide benefits including augmenting resources, quickening transportation responsiveness, and improving compliance with evacuation orders Chap. 3). Results indicate that sharing economy companies (i.e., Airbnb, Lyft, Uber) have been acting in disasters since 2012, and their actions have become more consistent and structured in since 2016 (Chap. 3). Private citizens are moderately willing to share shelter and transportation in hurricanes and wildfires (Chap. 3, Chap. 4). The percentage of survey respondents extremely willing to share transportation before evacuating was 29% for hurricanes and 37% to 48% for wildfires. For transportation during an evacuation, 24% were extremely willing to share for hurricanes and 59% to 72% for wildfires. Individuals were more willing to share housing for free than for a cost (Chap. 3., Chap. 4). About 19% were extremely willing to share housing for free for hurricanes, with 24% to 30% for wildfires. I also find spare capacity in terms of beds/mattresses (ranging from 84% to 90%) exists widely (Chap. 3, Chap. 4). Approximately 77% of evacuating vehicles from Hurricane Irma had at least two empty seats with a seatbelt (Chap. 3), and 64% to 69% of evacuating vehicles from the California wildfires had at least two empty seats with seatbelts (Chap. 4).

Regarding social equity, I find that while the sharing economy would be a feasible strategy for some vulnerable groups (e.g., carless, asset poor, older adults, people of color, immigrants), many vulnerable groups would experience significant barriers (e.g., digital divide; communication issues; liability for providers; high expense; locating evacuees; citizenship status) to accessing and using shared resources (e.g., physically disabled, unbanked, non-English speaking, homeless, undocumented immigrants) (Chap. 5). I also find that high levels of trust and compassion, as well as a sense of urgency, are associated with increased willingness to share resources, suggesting that some limitations related to the sharing economy could be overcome (Chap. 4). While past volunteers and community organization members in the surveys were more willing to share, other demographic variables (e.g., age, gender, income, race/ethnicity) had weak effects on willingness, indicating the primacy of trust and compassion in sharing behavior. Assuming a high trust/compassion population versus a low trust/compassion population results in a change of likelihood to share between 30% to 55%, depending on the sharing scenario (Chap. 4). Finally, I find substantial joint preferences between different evacuation sharing scenarios through a portfolio choice model and three unique classes (adverse sharers, interested sharers, and transportation-only sharers) with different sharing preferences through a multi-choice latent class choice model (Chap. 6). I find that families are unlikely to share regardless of model type and spare capacity has a weak positive influence on willingness to share. Demographic variables had sporadic effects depending on the chosen model, suggesting that the selection of discrete choice model can heavily influence results (Chap. 6).

(Joint) Choice Modeling Results: Through the development of portfolio choice models for hurricane and wildfire evacuations, I find that evacuation choices should be modeled jointly to account for correlation among choices and develop more nuanced transportation strategies for evacuations (Chap. 7, Chap. 8). For hurricanes (Chap. 7), joint preferences were especially strong between departure day and other choices (i.e., departure time of day, route) and between destination and other choices (i.e., transportation mode, route, shelter type). For wildfires (Chap. 8), strong joint preferences were found for departure day and other choices (i.e., departure time of day, destination, shelter type, transportation mode, route) and destination and other choices (i.e., departure time of day, shelter type, route). However, joint preferences are not always the same between the two wildfire cases (2017 December Southern California Wildfires and 2018 Carr Wildfire), suggesting that joint choice making is contextually, geographically, and/or culturally dependent.

I also find, via a latent class choice model, two classes of individuals for the decision to evacuate or stay in a hurricane (Chap. 7). A class of "keen evacuees" – composed of families, individuals living near the hurricane landfall area, and those with risk perceptions who were more likely to evacuate but could not be influenced by mandatory evacuation orders. A class of "reluctant evacuees" – comprised of previous evacuees, long-time residents, and those with concerns over evacuation logistic barriers – was much less likely to evacuate but could be influenced to leave through mandatory evacuation orders (Chap. 7). The decision to evacuate or stay/defend in a wildfire is influenced by mandatory evacuation orders and risk perceptions but with uneven influence of household and individual characteristics (Chap 8.). Finally, I developed a series of wildfire models, finding that attributes of departure times (e.g., immediate fire danger, pressure from neighbors to leave, uncertainty of escape route, visibility, visual fire level) and routes (e.g., distance, fire danger along route) influence choice making. (Chap. 9). However, attributes related to shelter type, transportation mode, and reentry timing were not influential, suggesting that demographics, risk perceptions, and/or resource availability may better explain those choices.

<u>Regret Minimization Results</u>: Finally, through a series of random utility maximization (RUM) and random regret minimization (RRM) models for wildfires (Chap. 9), I find regret minimizing behavior to be relatively weak for all considered choices (i.e., departure timing, route, transportation mode, shelter type, and reentry timing). Given my findings of weak attribute-level regret for departure timing, route, and reentry timing as well as weak class-oriented regret for route and transportation mode, I conclude that regret minimization does not explain behavior in evacuations better than utility maximization. However, results indicate that the survey construction and methodology could be significantly improved to better test the presence of regret minimizing behavior, and regret minimization should continue to be explored in evacuee choice making.

<u>Policy Recommendations</u>: Employing these results, I provide a series of recommendations to local and regional agencies to improve compliance, reduce congestion, and increase social equity. For example, a sharing economy strategy, regardless of hazard (based on Chap. 3 to 6), should: 1) develop low-tech communication and matching methods; 2) leverage neighborhood networks and community-based organizations to distribute resources to vulnerable groups; 3) connect with public transit plans; 4) incorporate significant input from vulnerable populations; and 5) combine both transportation and sheltering resources across all temporal points of the disaster. Based on hurricane choice modeling results (Chap. 7), agencies should be prepared to deploy transportation resources, responses, and services significantly before landfall, at night, and along highways. Agencies should also target mandatory evacuation orders in certain neighborhoods (previously evacuated zones, long-time residents) and leverage orders as an instrument to reduce concerns over evacuation logistic barriers to increase compliance. Agencies are recommended to also target mandatory evacuation orders for wildfires (Chap. 8), but orders need to be distributed more rapidly and through low-tech communication methods. Results also suggest that agencies should be prepared to rapidly deploy transportation responses at night, close to the evacuation zones (i.e., highly localized), and along arterial and local streets (Chap. 8, Chap. 9) Finally, agencies in wildfires should encourage people to leave before they can visually see the fire, increase evacuation information at the neighborhood level, and provide clear routing information (Chap. 9).

<u>Summary</u>: In this dissertation, I present several new pathways and research areas to better tackle three critical evacuation challenges related to compliance, congestion, and social equity. Through theoretical, methodological, and empirical contributions, I reinforce well-known and offer new evacuation strategies that can be implemented by governments faced with the complicated task of moving thousands and even millions of people. Ultimately, the research presented in this dissertation offers an academic building block and launching point for future work in the evacuation field, while also remaining grounded in the need for stronger practical applications of research to improve evacuation plans, strategies, and policies.

To God

Mom and Dad

Carolyn, Kevin, Chase, and Mira

Christy

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ii) Acknowledgements

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“If any of you lacks wisdom, you should ask God, who gives generously to all without finding fault, and it will be given to you.” James 1:5

Chapter 1: Introduction

1.1) Tackling Critical Evacuation Challenges

In major disasters, evacuations are one of the primary methods to safeguard human life from impending danger. Over the past five years, hurricanes in the United States (U.S.), including Irma, Florence, and Dorian, have required the evacuations of millions of people (Maul, 2018; Chappell and Domonoske, 2018; Johnson et al., 2019). Between 2017 and 2019, approximately 1.1 million people received mandatory evacuation orders spanning 11 California wildfires, often with minimal warning (Wong et al., 2020). Moreover, these large-scale disasters often obscure widespread evacuations for more localized, smaller events and other hazard types such as dam failures and chemical accidents. In 2019, thousands evacuated from massive flooding across the Midwest in mostly rural areas (CBS News, 2019), and approximately 180,000 people were ordered to evacuate during the 2017 Oroville Dam Crisis in rural California (Schmidt et al., 2017). Likewise, a 2019 explosion at a chemical plant in Port Neches, Texas led to mandatory evacuations of approximately 50,000 people (Ortiz, 2019).

For decades, researchers and practitioners have developed new strategies to evacuate people from natural and human-made hazards (Lindell et al., 2019). Despite these strategies, recent natural disasters – such as Hurricane Floyd in 1999, Hurricanes Katrina and Rita in 2005, and the Camp Fire in 2018 – have exposed the shortcomings of current communication and evacuation strategies in ensuring efficient and safe evacuations (Dow and Cutter, 2002; Boyd et al., 2009; Murray-Tuite and Wolshon, 2013; Nicas et al., 2018; Wong et al., 2020). These examples, along with many other disasters in the U.S., underscore three critical challenges in evacuations:

1) Persistent evacuation non-compliance to mandatory evacuation orders;
2) Poor transportation response, leading to heavy congestion, slow evacuation clearance times, and high evacuee risk; and
3) Minimal attention in ensuring all populations, especially those most vulnerable, have transportation and shelter.

As natural disasters and human-made events more severely impact populations due to factors including climate change, land development, and population shifts, local and regional governments across geography types (rural to urban) need to develop effective evacuation strategies that move all people to safety. The three challenges of compliance, congestion, and social equity each involves a diverse set of research needs and methodologies to provide recommendations. To tackle the challenges, this research conducts an examination of three innovative opportunities (Table 1):

1) the feasibility of the sharing economy and emerging mobility in evacuations;
2) the implications of evacuation choice making, particularly joint choices; and
3) the suitability of alternative decision rules, specifically regret, to describe evacuee choice making.

Employing data from individuals impacted by disasters in the U.S., this research aims to build more resilient communities to handle acute shocks (i.e., disasters and non-natural hazards), as they relate to transportation. Most importantly, the goal of this research is to develop empirically driven evacuation strategies for governmental agencies to prepare for, respond to, and recover from disasters.

Table 1: Intersection of Critical Evacuation Challenges and Dissertation Research Topics

	Compliance	Congestion	Social Equity
Sharing Economy		*	
(Joint) Choice Making			**
Regret Minimization			**

* Further research beyond this dissertation will be needed to determine the effects of the sharing economy (and public transit) on congestion during evacuations.
** While topics could feasibly address social equity, data on the choice making of vulnerable groups was not robust enough for any definitive conclusions.

1.2) Dissertation Topics and Contributions

This dissertation explores three innovative opportunities – the sharing economy, (joint) choice making, and regret minimization – to address three critical evacuation challenges related to compliance, congestion, and social equity. The following sections, divided by research topic, provide an overview of each topic and the contributions made in each chapter. First, the background is presented with a brief literature review to provide appropriate context. Next, the key gaps in the literature are outlined followed by a series of research questions. Finally, the research questions are answered through the contributions, which are described briefly through a manuscript-based approach.

1.2.1) The Sharing Economy

The sharing economy leverages advances in technology and communication to create online transactions through which goods and services are exchanged and shared (Hamari et al., 2016). While traditional sharing economy markets have focused on goods, new services in the mobility and homesharing sectors have provided innovative ways to travel and find housing. Indeed, today's new technological connections (i.e., expanded Internet, smartphone adoption), sharing economy platforms (i.e., Airbnb, Uber, Lyft), and emerging mobility and housing options (i.e., transportation network companies, ridehailing, carsharing, homesharing) offer potential and innovative tools for supplementing public resources and improving disaster response and recovery (Wong et al., 2018). Many cities lack the necessary resources and assets to sufficiently evacuate and shelter all citizens, especially for large-scale disasters. While public transit would be a preferred mechanism to transport a significant number of evacuees, many cities have not planned a public transit-based response, and some cities lack the assets and drivers needed in an evacuation (see Renne and Mayorga, 2018 for an overview). Consequently, resources through the sharing economy (either through private companies or private citizens) could supplement (but not supplant) public resources. In this way, the sharing economy could fill the gaps in effective evacuation response through providing rides and shelter for those who need it most, increasing the occupancy levels of evacuating vehicles, and relieving pressure on public shelters. At the same time, these potential benefits may be unevenly distributed. Issues pervasive in the sharing economy will likely continue during disasters, particularly related to access to the services and discrimination. Questions also remain on whether a supply (or demand) exists for these types of shared assets. Altogether, seven key research questions were developed to guide the research on the sharing economy in disasters:

1) What has been the role of the sharing economy in disasters?
2) What are the benefits and limitations of the sharing economy in evacuations, particularly the equity implications for specific vulnerable groups?
3) What is the magnitude of spare capacity in vehicles or houses to evacuate and shelter?
4) Are individuals willing to provide rides or shelter for evacuees?
5) What influences an individual to share transportation and housing resources in an evacuation, such as factors related to trust, compassion, and evacuation urgency?
6) Is willingness to share correlated between different sharing economy opportunities in evacuations? Are there unobserved classes of sharers and non-sharers that exhibit similar sharing preferences?
7) How do different model types using the same data uncover different behavioral nuances related to the sharing economy?

As the sharing economy has only been minimally studied in the context of disasters and evacuations (Wong et al., 2018; Li et al., 2018; Wong and Shaheen, 2019; Borowski and Stathopoulos, 2020), the most critical gap in literature is the lack of theoretical and empirical understanding of its feasibility in this unique context. Thus, this research proposes the concept of employing the sharing economy in evacuations and conducts a full exploration of this potential strategy (including significant limitations) by examining:

- Current state of the sharing economy in evacuations, benefits and limitations of the sharing economy in disasters, and the willingness of individuals to provide shared resources (Chapter 3);
- Influence of different factors, including trust and compassion, on willingness to share transportation and sheltering in a disaster (Chapter 4);
- Extent to which sharing economy platforms and shared resources can benefit or limit social equity for vulnerable populations in evacuations (Chapter 5); and
- Behavioral nuances of different models, including the latent classification and joint modeling of individuals to share resources in multiple evacuation scenarios for transportation and sheltering (Chapter 6).

Across these chapters, policy recommendations for agencies are provided to build a structured and data-driven strategy for leveraging shared resources from both companies and private individuals. This research also offers new directions of inquiry related to emerging mobility that could successfully address or adversely affect the three ongoing evacuation challenges of compliance, congestion, and social equity.

1.2.2) (Joint) Choice Modeling in Evacuations

Individuals in hazards must make multiple, complex choices that have important effects on the transportation system. This includes the decision to evacuate or stay followed by a series of transportation-related choices of departure time, route, destination, transportation mode, shelter type, and eventually reentry time. These various choices have been studied extensively for hurricanes using both simple and more advanced discrete choice models that are grounded in utility maximization (for example, Riad et al., 1999; Whitehead et al., 2000; Deka and Carnegie, 2010; Hasan et al., 2011; Sadri et al., 2015).

Despite the many improvements in understanding evacuation choice making, five key gaps remain in the field. First, the majority of discrete choice studies have focused on hurricane behavior, but it is unlikely that choice making is consistent across hazards with varying spatial, temporal, and risk characteristics. A wide gap in choice making research particularly exists for wildfire behavior, despite the recent and severe impacts of these events in California (see Toledo et al., 2018; McCaffrey et al., 2018; Lovreglio et al., 2019 for the only wildfire modeling examples). Second, most choice making studies have focused on the decision to evacuate or stay, rather than other key evacuation choices (e.g., route, transportation mode, destination) that influence transportation response in a disaster. While some work has been done for hurricanes (e.g., Cheng et al., 2008; Gudishala and Wilmot, 2012; Mesa-Arango et al., 2013; Sadri et al., 2014a; Sadri et al., 2014b), no studies have employed discrete choice modeling to understand these choices in a wildfire evacuation. Third, only minimal work has been conducted in determining the extent that evacuees and non-evacuees can be segmented based on unobserved variables using latent class choice models (LCCMs) (see Urata and Pel, 2018; McCaffrey et al., 2018 for the only examples). Indeed, these models could help identify how different classes of people make choices in evacuations and thereby provide additional behavioral understanding to improve transportation response. Fourth, post-disaster research has yet to consider the role of attributes of alternatives in evacuations, relying solely on risk perceptions, demographic variables, and hazard characteristics. Capturing attributes of alternatives in a revealed preference setting will require new survey methodologies for constructing choice-sets. Finally, and most importantly for this dissertation, evacuation choices have yet to be considered jointly as a multi-dimensional decision. After an individual decides to evacuate, they are faced with a choice composed of concurrent decisions of departure day, departure time of day, destination, shelter type, transportation mode, and route. While work has been conducted on two choices (for example Fu and Wilmot, 2004; Bian, 2017; Gehlot et al., 2018), research has yet to expand this to additional dimensions or to consider if other pairs of choices (e.g., route and destination; shelter type and departure day; transportation mode and departure time of day) exhibit correlation. These gaps in the literature guided the development of five broad research questions:

1) What influences choice making in evacuations, particularly choices beyond the decision to evacuate or stay and especially for wildfire evacuations?
2) Do mandatory evacuation orders influence different unobserved classes of people? What characteristics are associated with these classes?
3) What choices in evacuations (specifically for hurricane and wildfire evacuations) are correlated and dimensionally dependent? How should choices be modeled to test and not restrict dimensional dependency?
4) How do different joint model types using the same data uncover different behavioral nuances?
5) How do attributes of alternatives affect choice making in evacuations?

As a note, these research questions are applicable for hazards beyond hurricanes and wildfires and can inform behavioral modeling approaches and studies for all hazard types. Indeed, further work will be necessary to determine the similarity of behavior across hazards, along with different geographies and cultures. For now, to address the literature gaps and tackle the evacuation challenges of compliance and congestion, this research explores choice making and joint choice making in evacuations as it relates to hurricanes and wildfires by studying:

- Joint preference of sharing through transportation and sheltering scenarios linked by a latent classification of individuals and dimensional dependency (Chapter 6);
- Latent classification of individuals for the decision to evacuate or stay and decision-dimensional dependency of hurricane choices (departure day, departure time of day, destination, shelter type, transportation mode, and route) using a portfolio choice model (Chapter 7);
- Decision-dimensional dependency of wildfire choices (departure day, departure time of day, destination, shelter type, transportation mode, and route) using a portfolio choice model (Chapter 8); and
- Attribute-based assessment of wildfire evacuation choices beyond the decision to evacuate or stay (Chapter 9).

For these chapters, transportation response recommendations are directly tied to the modeling results, which show intuitive yet subtle behavioral patterns. Moreover, this research identifies choices that are more likely to be correlated, encouraging deeper exploration into the interactions between decision dimensions and their implications for transportation response to reduce congestion and improve evacuation outcomes.

1.2.3) Regret Minimization

For past choice modeling research described in the previous section, discrete choice models were developed assuming that an individual maximizes their utility (or satisfaction) via a linear-additive form of parameters. The associated error-inclusive random utility maximization (RUM) model has been widely applied across transportation (Ben-Akiva and Lerman, 1985; Train, 2009) and the evacuation field. However, alternative decision rules such as regret minimization and the error-inclusive random regret minimization (RRM) models (Chorus et al., 2008; Chorus, 2010) may better explain behavior in an evacuation context. Indeed, research has found that "anticipated regret is experienced when decisions are difficult and important and when the decision-maker expects to learn the outcomes of both the chosen and rejected options quickly" (Zeelenberg and Pieters, 2007). These criteria for anticipated regret fit disaster and evacuation situations well, suggesting that RRM may better explain evacuee behavior than traditional RUM models. To address this potential, An et al. (2015) developed a hypothetical stated preference (SP) survey for flooding in Harbin, China. The research found that RRM models (in several forms) slightly outperformed RUM models (An et al., 2015). Similarly, Wang et al. (2017) developed an SP survey for the same flooding event in Harbin, China but focused on route choice. Model results indicated that the RRM and a hybrid utility-regret model outperformed RUM. These two studies are the only examples of employing RRM methodology in the context of evacuations. Moreover, neither of these studies considered *actual* evacuation behavior, which may differ significantly from *stated* evacuation behavior. To capture actual evacuation behavior, revealed preference (RP) surveys need to be developed. Research has found that RP surveys are highly applicable for contexts with situational and personal constraints such as a dangerous choice environment or emotion-driven choices (Morikawa, 1989; Louviere et al., 2000). Moreover, SP data often exhibit biases of overstatement, understatement, and/or indifference, which is rarely present in RP data (Morikawa, 1989; Hausman, 2012).

In the evacuation field, most research has focused on using traditional RUM models to assess behavior (including the research in Chapters 4, 6 - 8). However, given that regret has been found to influence decision-making in situations where choices are hard and important, lead to rapid feedback, and require accountability, regret minimizing behavior may be present in evacuation choice making. With this hypothesis, two research questions were developed:

1) What methodology should be used in a revealed preference setting to reconstruct challenging choice-sets with near endless alternatives and unknown attributes of alternatives?
2) Does random regret minimization (RRM) better describe evacuation behavior than traditional random utility maximization (RUM)?

The alternative decision rule related to regret theory and associated RRM models may not only outperform traditional RUM models, but it could uncover unique behaviors that have key implications for improving transportation response. To open this new area of exploration and inquiry in evacuee choice making using alternative decision rules, this dissertation answers the two research questions by exploring and testing:

- Regret minimizing behavior of wildfire evacuees by developing a revealed preference (RP) methodology for challenging choice-sets (Chapter 9).

For this chapter, RUM and RRM-based models are compared across wildfire evacuation choices using RP data. Along with several policy recommendations to improve transportation response outcomes, this assessment also offers a comprehensive analysis of the limitations of RP data for building RRM models. While the connection of RRM to critical evacuation challenges – compliance and social equity – remains mostly unknown, this research aims to open a new topic of literature that challenges pre-conceived modeling assumptions. Further assessment will be necessary to determine if RRM outperforms and better explains behavior than RUM models, which might ultimately improve understanding of evacuee behavior.

1.3) Empirical Contributions

Beyond the above theoretical and methodological contributions in the topics of the sharing economy, (joint) choice modeling, and regret minimization, this research offers significant empirical contributions that underscore the need for primary data collection. Given the irregular occurrence of disasters and evacuations, collecting empirical data is often a sporadic process without consistent funding sources. While some data sources exist for hurricane behavior, data are sparse for wildfires, making it difficult to assess behavior in this disaster context. This is due in part to smaller wildfire evacuations that occur with less frequency (as compared to hurricanes). At the same time, agencies and impacted individuals are primarily concerned with response and recovery, making research partnerships challenging. Despite these issues, survey data from individuals impacted by disasters are critically important, as they reveal actual behavior for a rare choice context that may only be experienced once to several times during a lifetime. To contribute empirically to the evacuation field, this research collected online survey data from multiple disasters including:

- 2017 Hurricane Irma in Florida (n=645);
- 2017 December Southern California Wildfires (n=226); and
- 2018 Carr Wildfire (n=284).

An online survey methodology was chosen to quickly and cost-effectively reach a wide population of individuals impacted by the three disasters. This methodology also permitted a more complex survey structure and allowed those displaced by the disaster to respond. Despite these clear benefits, this online survey approach (as explained throughout the following chapters) has a number of limitations, most notably self-selection bias and underrepresentation of some hard-to-reach populations (e.g., low-income, Spanish-speaking, individuals with disabilities, low education, carless). Since these online surveys missed vulnerable groups, and agencies struggle with ensuring equitable outcomes in evacuations, we conducted four focus groups (n=37) composed of vulnerable groups impacted by California wildfires (2017 October Northern California Wildfires, 2017 December Southern California Wildfires, 2018 Mendocino Complex Fire). These focus groups – low-income individuals, older adult, individuals with disabilities, and Spanish-speaking individuals – offer a much-needed perspective to better understand the equity implications of evacuations, particularly for the sharing economy.

1.4) Dissertation Structure

This dissertation uses a manuscript-based approach to provide theoretical, methodological, and empirical contributions to the evacuation field (summary provided in Table 2). The research begins with the creation, development, and analysis of the sharing economy strategy (Chapters 3 - 6), which could increase compliance to evacuation orders and improve social equity for vulnerable populations in any hazard. A thorough feasibility assessment is provided, including the many limitations that remain for implementing a sharing economy strategy in disasters. Next, the dissertation develops a series of choice models, in particular joint choice models, for multiple evacuation decisions (Chapters 6 - 9). These chapters also explore more traditional discrete choice models to provide behavioral insights and nuance for improving the effectiveness of mandatory evacuation orders and reducing congestion. Then, the dissertation offers a theoretical alternative to utility maximization by building a revealed preference methodology to assess regret minimization in evacuations (and other challenging choice contexts) and developing models for multiple evacuation choices (Chapter 9). This chapter also provides additional behavioral understanding for improved evacuation strategies. Finally, the dissertation presents conclusions, associated recommendations, a comparison of hurricane and wildfire behavior, and a series of new research directions for the growing field of evacuations (Chapter 10).

Table 2: Summary of Theoretical, Empirical, and Methodological Contributions

Chapter	Chapter Title	Contributions		
		Theoretical	Methodological	Empirical
3	Bridging the Gap Between Evacuations and the Sharing Economy	Feasibility of the sharing economy via private companies or citizens to be leveraged to increase resources in evacuations	None	30+ cases of sharing economy actions Sharing economy willingness and actual usage from 2017 Hurricane Irma
4	Trust and Compassion in Willingness to Share Mobility and Sheltering	Influence of trust and compassion on willingness to share	None	Sharing economy willingness and actual usage from

	Resources in Evacuations: A Case Study of the 2017 and 2018 California Wildfires	resources in an evacuation		2017 Southern California Wildfires and 2018 Carr Wildfire
5	Can Sharing Economy Platforms Increase Social Equity for Vulnerable Populations in Disaster Response and Relief? A Case Study of the 2017 and 2018 California Wildfires	Social equity benefits and limitations of the sharing economy in evacuations	None	Vulnerable population focus groups for low-income, older adult, individuals with disabilities, and Spanish-speaking from 2017-2018 California wildfires
6	Understanding the Willingness to Share Resources in a Hurricane Evacuation: A Multi-Modeling Approach	Joint preference among related sharing scenarios	Multi-modeling approach to assessing behavior	Sharing economy willingness and actual usage from 2017 Hurricane Irma
7	Fleeing from Hurricane Irma: Empirical Analysis of Evacuation Behavior Using Discrete Choice Theory	Latent classification of individuals based on evacuation order and joint preference (i.e., decision-dimensional dependency) among evacuation choices	Development of portfolio choice model	Choice behavior from a survey of individuals impacted by 2017 Hurricane Irma
8	Understanding California Wildfire Evacuee Behavior and Joint Choice Making	Joint preference (i.e., decision-dimensional dependency) among evacuation choices	Development of portfolio choice model	Choice behavior from a survey of individuals impacted by the 2017 Southern California Wildfires and 2018 Carr Wildfire
9	A Revealed Preference Methodology to Evaluate Regret Minimization with Challenging Choice Sets: A Wildfire Evacuation Case Study	Choice making in evacuation situations (where choices are difficult, important, and require accountability) by minimizing regret rather than maximizing utility	Development of a revealed preference survey methodology; development of regret-based models	Choice behavior from a survey of individuals impacted by the 2017 Southern California Wildfires

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Chapter 2: Background, Context, and Governance

2.1) Exploring New Strategies

To begin examining the three primary topics of – the sharing economy (joint), choice modeling in evacuations, and regret minimization – additional literature and definitions are provided, offering a baseline context for the remainder of the dissertation. These three different topics offer an opportunity to consider, analyze, and generate new strategies to improve evacuations as they relate to improving compliance, decreasing congestion, and building social equity. Further details and studies related to each area can also be found in later chapters.

2.1.1) The Sharing Economy

The sharing economy is an economic model where businesses-to-peer (B2P) and/or peer-to-peer (P2P) goods and services are exchanged online via the Internet. Also known as "collaborative consumption," the sharing economy has been facilitated by the rapid development of information and communications technology (ICT), which allows the sharing economy to operate predominately through technological platforms such as websites or mobile phone applications (Botsman and Rogers, 2010; Hamari et al., 2016). Frenken et al. (2015) and Frenken and Schor (2017) also provide a useful definition of the sharing economy where "consumers grant each other temporary access to under-utilized physical assets ('idle capacity'), possibly for money." It should be noted that the sharing economy relies heavily on trust (i.e., confidence placed in a person to provide benefit or be reliable), particularly of strangers (Belk, 2010; Hawlitschek et al., 2016). While altruism (i.e., selfless concern for the well-being of others) may play a role in the sharing economy (Hamari et al., 2016), compassion (i.e., sympathy and concern for the sufferings of others) has yet to be linked to collaborative consumption under normal conditions.

The exchange of money for goods and services, particularly for B2P transactions, has led to a deviation from original participation in collaborative consumption, which arose from an obligation to do good, help others, be more sustainable, or build community (Albinsson and Perera, 2012; Prothero et al., 2011; Belk, 2014; Hamari et al., 2016). While economic benefits of the sharing economy through the rise in income and consumer welfare have been documented, the social and environmental benefits (and who benefits economically) have been largely unclear (Frenken and Schor, 2017). These concerns point to complex and layered benefits and limitations of the sharing economy that have varied effects on different people. For example, Zervas et al. (2017) found that hotel earnings declined in places where Airbnb (a homesharing platform where people rent their home or space for a cost) increased, indicating that hotel employees may experience a decrease in benefits. Research on homesharing has found some evidence of racial discrimination related to bookings and listings (Edelman and Luca, 2014; Wang et al., 2015; Edelman et al., 2017). Other work has found potential evidence of uneven influences of homesharing on the rental market, which may contribute to gentrification (both direct displacement and exclusionary displacement) in certain neighborhoods in New York City (Wachsmuth and Weisler, 2018).

A similar story has played out in transportation, where a number of sharing economy companies and services have become established modes of transportation. The key areas of shared mobility are reviewed in Shaheen et al. (2020), and this research is incorporated into Table 1, which offers additional details on the structure and definition of the key areas. Many studies of shared mobility have found benefits including lower costs, higher convenience, reduced usage of personal vehicles, and lower greenhouse gas (GHG) emissions (Cervero and Tsai, 2004; Martin and Shaheen, 2011; Shaheen and Chan, 2015; Martin and Shaheen, 2016; Rayle et al., 2016; Chen and Kockelman, 2016; Feigon and Murphy, 2016; Clewlow and Mishra, 2017; Brown, 2018; Shaheen and Cohen, 2019). Despite this literature, considerably more research is needed to determine the full benefits and limitations of shared mobility. In fact, a number of limitations of shared mobility have already been documented. Many travelers face significant equity barriers (such as economic or physiological dimensions) that can prevent them from accessing or using shared mobility (Shaheen et al., 2017). TNCs have been found to increase vehicle miles traveled (VMT) in New York City and San Francisco and likely contribute to congestion (Schaller, 2017a; Schaller, 2017b; SFCTA, 2017). Research has also found that TNC riders experience various forms of racial and gender discrimination in ride requests, length of trips, and cancellations (Ge et al., 2016). Research on bikesharing has found mixed results, with limitations including unequal distribution of benefits and minimal impact on reducing GHG emissions or congestion (Ricci, 2015). Additionally, bikesharing (and by extension scooter sharing) have GHGs associated with manufacturing, rebalancing, operation (particularly if electric), maintenance, and disposal (Luo et al., 2019).

Beyond these limitations, additional concerns have been raised about the sharing economy related to perpetuating class, gender, and racial biases; exploiting labor; shifting risks from companies to contractors; eroding legacy businesses (e.g., taxis, hotels); increasing greenhouse gas emissions; and failing to increase social capital (Schor, 2016). The sharing economy – particularly transportation companies – has waged an ongoing fight with governments over regulations (Rauch and Schleicher, 2015). Concerns over labor exploitation have pushed states including California to enact legislation (AB 5, 2019) to reclassify "gig economy" workers as employees (rather than independent contractors) with corresponding employee benefits. Even as consumers of the sharing economy have largely benefited, the debate over the sharing economy, particularly related to regulation, remains fierce (Schor and Cansoy, 2019).

Table 1: Key Areas of Shared Mobility with Associated Definitions and Key Examples (Adapted from Shaheen et al., 2020)

Shared Mobility Area	Definition	Examples
On-Demand Ride Services ▪ Transportation Network Companies (TNCs) ▪ Ridesplitting/Pooling ▪ E-Hail	On-demand access to car rides where users can request a trip via a smartphone application and where riders are charged based on distance and travel time	Uber; Lyft; Flywheel
Ridesharing ▪ Carpooling ▪ Vanpooling	Grouping of travelers into a private automobile for trips between home and work locations or for trips that would have otherwise occurred	Scoop; Waze Carpool
Microtransit ▪ Fixed route and fixed schedule ▪ Flexible route and flexible schedule	Public transit service, often enabled by technology, that can allow for fixed and/or flexible routes and/or on-demand scheduling	Via, AC Transit Flex
Bikesharing ▪ Station-Based ▪ Dockless ▪ Hybrid	On-demand access to bicycles at a variety of pick-up and drop-off locations for one-way or roundtrip travel	JUMP; Bay Wheels; Citi Bike

Scooter Sharing ▪ Station-Based ▪ Dockless ▪ Hybrid	On-demand access to electric scooters at a variety of pick-up and drop-off locations for one-way or roundtrip travel	Bird; Lime; Spin
Carsharing ▪ Roundtrip ▪ One-Way ▪ Personal Vehicle Sharing	Short-term access to automobiles, allowing users to gain the benefits of a private automobile while forgoing auto ownership costs	Zipcar; GIG Car Share; Turo
On-Demand Delivery Services ▪ P2P courier services ▪ Paired on-demand passenger ride and courier services	For-hire delivery services through connected couriers with their personal vehicles for monetary compensation	DoorDash; UberEATS; Postmates

2.1.2) (Joint) Choice Modeling in Evacuations

Evacuations require a series of complex choices that can heavily affect the transportation system and influence the appropriate response by agencies. First, people must make the decision of whether to evacuate or stay. One key issue is that not all individuals comply with mandatory evacuation orders (non-compliance), while others will leave without receiving a mandatory order (shadow evacuations). To determine the influence of various factors or parameters (e.g., characteristics of the decision-maker, hazard characteristics, attributes of alternatives) on evacuation choices, the field has employed discrete choice analysis. This statistical and econometric method determines the quantitative influence of a series of independent variables (characteristics of the decision-maker or alternatives) on an outcome, which is modeled as a dependent variable (a decision-maker's choice). Most research has modeled behavior by assuming individuals maximize their utility (or satisfaction), which is specified as a linear function of parameters. The error-inclusive random utility maximization (RUM) model has been the primary behavioral modeling form across transportation choices, including evacuations (see Ben-Akiva and Lerman, 1985; Train, 2009; Washington et al., 2010 for full explanations of discrete choice modeling). RUM models have been widely used since they possess statistical properties that produce relatively simple, accurate, and tractable solutions. Moreover, RUM models allow for simple comparison of how an individual engages in tradeoffs that influence their choice. The traditional binary and multinomial logit modeling forms (using a logistic function with an Extreme Value Type I distribution) have been the most widely used models, largely due to the ease of calculation, simple probabilistic structure, and easily interpreted results. Recently, research in behavioral analysis (including beyond transportation) has developed other discrete choice models that vary the underlying statistical distribution, structure of probabilistic error terms, and/or interaction of independent variables to better explain and model behavior. Several examples of this progression are provided below in Table 2. Walker (2001) and Train (2009) provide comprehensive explanations of most of these discrete choice models, including their variations.

The evacuation field has employed different discrete choice models to explain decisions that people must make in hazards. Most studies on the decision to evacuate or stay have used data collected from survey responses of individuals impacted by disasters (i.e., revealed preference data) to build mostly traditional binary logit and multinomial logit models (Riad et al., 1999; Whitehead et al., 2000; Wilmot and Mei, 2004; Zhang et al., 2004; Smith and McCarty, 2009; Deka and Carnegie, 2010; Solis et al., 2010; Stein et al., 2010; Hasan et al., 2011; Hasan et al., 2012; Huang et al., 2012; Murray-Tuite et al., 2012; Xu et al., 2016; Yin et al., 2016; McCaffrey et al., 2018; Sarwar et al., 2018; Toledo et al., 2018; Wong et al., 2018; Lovreglio et al., 2019). Along with the decision to evacuate or stay, a number of other evacuation choices have also been modeled, almost exclusively for hurricane evacuations, using discrete choice analysis of: departure timing (Gudishala and Wilmot, 2012; Hasan et al., 2013; Ng et al., 2015); destination (Cheng et al., 2008); shelter choice (Whitehead et al., 2000; Smith and McCarty, 2009; Deka and Carnegie, 2010; Mesa-Arango et al., 2013); transportation mode choice (Deka and Carnegie, 2010; Sadri et al., 2014a); route choice (Sadri et al., 2014b; Akbarzadeh and Wilmot, 2015; Sadri et al., 2015); and reentry compliance (Siebeneck et al., 2013). A number of these studies have also employed discrete choice models beyond traditional logit models, particularly related to mixed logit models (see Table 2). More recently, latent class choice models (LCCMs) have been employed to understand wildfire (McCaffrey et al., 2018) and tsunami (Urata and Pel, 2018) evacuation behavior by segmenting people based on unobserved characteristics. However, the development of LCCMs to explain evacuation behavior remains limited.

Table 2: Examples of Discrete Choice Models that Vary from Traditional Binary and Multinomial Logit Models

Discrete Choice Model	**Difference from Binary/Multinomial Logit**	**Example Literature in Evacuations**
Mixed Logit	Allows for random taste variation, correlation of unobserved factors over time, and unrestrictive substitution patterns (Train, 2002)	Hasan et al. (2011); Yin et al. (2016); Hasan et al. (2013); Sadri et al. (2014b); Sadri et al. (2015)
Nested Logit	Allows for correlation over alternatives through a substitution pattern where alternatives can be partitioned into subsets (i.e., nests) (Train, 2002)	Gudishala and Wilmot (2012); Mesa-Arango et al. (2013); Sadri et al. (2014a); Bian (2017); Bian et al. (2019)
Ordered Logit	Models ordered responses, which addresses the pattern of similarity and dissimilarity of alternatives close to each other (Train, 2002)	Deka and Carnegie (2010); Ng et al. (2015)
Sequential Logit	Models decisions over time as interdependent to allow for the influence of time-dependent factors (Fu and Wilmot, 2004)	Fu and Wilmot (2004); Fu et al., (2006); Gudishala and Wilmot (2012)
Probit	Allows for correlation over alternatives and time by assuming that unobserved factors are distributed jointly normal (Train, 2002)	Solis et al. (2010); Xu et al. (2016)
Latent Class	Captures latent (unobserved) segmentation in terms of taste parameters, choice sets, and/or decision protocols (Walker, 2001)	McCaffrey et al., (2018); Urata and Pel (2018)
Portfolio	Captures correlations (if present) between dimensions of choices without imposing a choice hierarchy or sequencing (Dellaert et al., 1997)	None

Another key advancement in evacuation literature has been to consider evacuation choices sequentially or jointly. Fu and Wilmot (2004) and Fu et al. (2006) developed a sequential logit model in which departure timing was considered immediately following the decision to evacuate or stay. This ordering was removed in Gudishala and Wilmot (2012), which developed a time-dependent nested logit model. Bian (2017) and Bian et al. (2019) developed nested logit models to jointly estimate transportation mode and destination type, while Gehlot et al. (2018) estimated a joint discrete-continuous departure model for departure timing and travel times. Most recently, Damera et al. (2019) estimated a nested logit model for evacuation destination and accommodation type. All these studies, solely focusing on hurricanes, found significant correlation between the modeled choice dimensions, signifying that hurricane evacuation choices (and perhaps choices in other hazards) should be considered jointly. However, all these studies focus only on pairs of evacuation choices (rather than multiple dimensions), and many pairs have yet to be explored.

2.1.3) Regret Minimization

Regret is an emotional reaction, typically of sadness, remorse, or disappointment, over something that has happened or an action. Regret theory, developed by Loomes and Sugden (1982), posits that psychological feelings of regret and rejoice (specific terminology in this research) can be elicited based on the outcomes of an individual's choice between two options, A and B. If an individual chooses option A, but a more desirable outcome existed for option B, the individual may experience regret. The individual "may reflect on how much better their position would have been, had they chosen differently" (Loomes and Sugden, 1982). In other words, a decision-maker will feel a certain level of regret if their choice falls short of expectations, as compared to all other options. Alternatively, if an individual chooses option A, and option A has a more desirable outcome, the individual may experience rejoice.

To extend this regret theory using statistical techniques in discrete choice that mirror the linear-additive utility maximization (Ben-Akiva and Lerman, 1985), Chorus et al. (2008) and Chorus (2010) developed a model for multinomial choice sets and multiple attributes, postulating that decision-makers will minimize their anticipated regret when making a choice (i.e., regret minimization). Regret minimization also posits that regret receives more weight than rejoice due to an avoidance of negative emotion (i.e., regret aversion) (Chorus et al., 2008). This regret aversion feature of random regret minimization (RRM) models is conceptually similar to the notion of losses looming larger than gains. Mathematically, this theory leads to a convex regret function that allows for semi-compensatory behavior in which the improvement of an attribute does not necessarily offset the poor qualities of another (and vice versa). The result is that poor performing attributes are penalized more than in traditional error-inclusive random utility maximization (RUM) models. In the error-inclusive RRM models, compromise alternatives that do well across all attributes are more attractive than extreme alternatives that may perform strongly in some attributes but very poorly in others (Chorus, 2010). RRM models are estimated using similar statistical techniques in econometrics as RUM models, are tractable, and are similarly parsimonious to linear-additive RUM models (Chorus, 2010; Chorus, 2012a, 2012b). The RRM model has also been extended via:

1) RUM-RRM models that add demographic characteristics (Chorus and Kroesen, 2014);

2) μRRM models that incorporate an estimable regret aversion parameter (μ) that is potentially attribute specific or latent class specific (Van Cranenburgh et al., 2015); and

3) Mixed decision latent class choice models (MDLCCM) in which decision-makers may be divided in terms of the decision rule (i.e., regret or utility) that best describes their behavior (RRM or RUM) (Hess et al., 2012; Hess and Stathopoulos, 2013).

Along with studies developing RRM (Chorus, 2010; Chorus, 2012a, 2012b), research has explored comparisons between RRM and RUM for transportation choices including: 1) travel mode (Hensher et al., 2016; Guevara and Fukushi, 2016; Anowar et al., 2019), 2) carsharing (Kim et al., 2017), and 3) vehicle route choice (Prato, 2014; Ramos et al., 2014; Guevara and Fukushi, 2016). An in-depth review of RRM modeling for mode and route choice is presented in Jing et al. (2018). Across these studies, RRM (for some or all attributes) outperforms RUM in about two-thirds of cases in terms of model fit and out-of-sample predictions, signifying strong explanatory power of RRM models. Despite this work in RRM, only two studies have explored regret minimization for evacuations (An et al., 2015; Wang et al., 2017) and both use a stated preference survey, which fails to capture actual behavior. Considerably more is necessary to determine if individuals make decisions by minimizing regret or maximizing utility in evacuations and disaster contexts.

2.2) Critical Evacuation Challenges

Evacuations are an important tool to save lives in disasters, reduce search and rescue operations, and improve quality of life. In the U.S., a significant number of large evacuations have occurred in the past several years from hurricanes (Maul, 2018; Chappell and Domonoske, 2018; Johnson et al., 2019), wildfires (Wong et al., 2020), and human-made events (Schmidt et al., 2017; Ortiz, 2019). Some natural events are predicted to worsen over the coming decades. The U.S. Global Change Research Program, a collaborative research effort by 13 federal entities, found significant increases in the intensity and frequency of rainfall, the frequency of heatwaves, and the number of wildfires in the U.S. due to climate change (USGCRP, 2017). Some storm types including hurricanes, tornadoes, and winter storms have been linked to climate change, but current research has not allowed for a detailed understanding or strong consensus (Reidmiller et al., 2018). Regardless, the economic toll of disasters has substantially increased in the U.S., also due in part to non-climate factors including land development and population increases in high-risk areas (Reidmiller et al., 2018). Indeed, for each year between 2015 and 2019, ten or more "billion-dollar weather and climate disasters" impacted the U.S., totaling $531 billion over five years (NOAA National Centers for Environmental Information, 2020). The increasing occurrence and intensity of disasters in the U.S. point to a future of ever larger and more frequent evacuations. The ramification is that critical evacuation challenges – compliance, congestion, and social equity – will become increasingly complex and difficult to overcome. To provide additional background and set the context for the remainder of this dissertation, each challenge is explained in more detail, including definitions and relevant literature.

2.2.1) Compliance and Evacuation Orders

An evacuation order (or notice) is a statement provided by an official entity (typically a government entity) notifying an individual that they should leave a specific geographic area due to a hazard. Evacuation orders are commonly divided into two categories: 1) mandatory evacuation orders and 2) voluntary/recommended evacuation orders. Entities also issue shelter-in-place orders, which instruct people to remain in a single location, usually inside (Lindell et al., 2019). A mandatory evacuation order connotes a severe need to depart due to the risks of the hazard. Currently, FEMA defines a mandatory evacuation as “a warning to persons within the designated area that an imminent threat to life and property exists and individuals *must*[1] evacuate in accordance with the instructions of local officials” (FEMA, 2010). Voluntary or recommended evacuation orders (sometimes called precautionary, highly recommended, or highly suggested evacuations) hold no legal enforcement. FEMA defines voluntary evacuations as “a warning to persons within a designated area that a threat to life and property exists or is likely to exist in the immediate future. Individuals issued this type of warning or order are *not required*[2] to evacuate; however, it would be to their advantage to do so” (FEMA, 2010).

Evacuation compliance refers to a complete evacuation from a hazardous area that was issued a mandatory evacuation order. Individuals who are issued mandatory evacuation orders but do not evacuate are considered non-compliant. In a review of evacuation compliance, Lindell et al. (2019) notes that a fully compliant population is extremely rare. Research has found a significant range of compliance for hurricanes, with most studies ranging from 34% to 65% for compliance (Riad et al., 1999; Prater et al., 2000; Dow and Cutter, 2002). More recent studies have found compliance around 49% for Hurricane Sandy in New York City (Brown et al., 2016) and 69% for Hurricane Irma in Florida (Wong et al., 2018). Recent research for wildfires has found compliance ranging from approximately 87% to 97% for mandatory evacuation orders, an improvement over hurricane evacuations, but still not 100% (Wong et al., 2020). Compliance to mandatory evacuation orders is not only a function of freedom of choice. In some cases, residents do not have the resources to evacuate, as occurred during Hurricane Katrina in 2005 (Wolshon, 2002; Renne, 2006). Similarly, research on Hurricane Irma found that 14% of non-evacuees did not have enough money to evacuate (Wong et al., 2018). The same research found that some non-evacuees did not want to sit in traffic or wanted to remain and protect their property. Noncompliance in wildfires has been found to be highly related to the desire to defend property from the fire (McCaffrey and Rhodes, 2009; McCaffrey and Winter, 2011; McLennan et al., 2018).

These many studies (and prior disasters) point to the overarching concern that some people will not evacuate even if they are ordered to do so. This issue presents a clear safety risk, as staying in an evacuation zone can lead to severe injuries and even loss of life. Equally problematic, people who remain in evacuation zones but need assistance will divert more resources to search and rescue operations, increasing risks for first responders. While the reasons for not evacuating are numerous (e.g., communication issues, risk perceptions, resource deficiencies), the need to increase compliance rates remains a key challenge in the evacuation field.

2.2.2) Congestion and Transportation Response

Congestion (e.g., traffic congestion) refers to the condition of semi-restricted or restricted flow of vehicles on a facility (e.g., road, highway). This condition is characterized by lower speeds, higher density of vehicles, and queuing of vehicles (Daganzo, 1997). For the purpose of evacuations, congestion is heavily tied to evacuation time estimates or ETEs (also referred to as evacuation clearance time), which is the time it takes for a population to evacuate a geographical area safely

[1] Emphasis from source
[2] Emphasis from source

(Lindell and Perry, 1992; Urbanik, 1994; Lindell and Prater, 2007). For example, a traffic accident along the evacuation route (i.e., an impediment on the roadway leading to decreased roadway capacity) would cause congestion and delay, leading to higher ETEs. This could in turn reduce the safety of individuals in the queue, whether endangering evacuees who may still be in an unsafe geographical area or reducing access to resources (e.g., food, water, gasoline).

Congestion has become a critical challenge in evacuations, as evidenced by Hurricane Floyd in 1999, Hurricane Rita in 2005, and the 2007 Southern California Wildfires (Lindell et al., 2019). It is estimated that over 2.5 million people were ordered to evacuate from Hurricane Floyd, and some evacuees experienced travel time increases of ten times over normal conditions (Dow and Cutter, 2002). Research found a general decrease of flows on roadways (Wolshon, 2001) along with rapid loading of roads, multi-vehicle evacuations, and conflicts of evacuees traveling in different directions (Dow and Cutter, 2002). The evacuation prior to Hurricane Rita also produced major traffic and congestion issues. Due in part to the deadly impact of Hurricane Katrina (Blumenthal and Barstow, 2005; Zhang et al., 2007), over 2.5 million evacuated for Hurricane Rita (including many in safe areas) leading to severe congestion. Accidents, heat exhaustion, and carbon monoxide poisoning during the Hurricane Rita evacuation caused 55 indirect deaths, far exceeding the seven fatalities from the storm itself (Knabb et al., 2006). Hurricane Rita also highlighted the need for vital in-route services including food, water, fuel, and towing (Murray-Tuite and Wolshon, 2013).

Major congestion has also occurred during wildfire evacuations. In 2018, the Camp Fire in Paradise, California led to severe congestion caused by road blockages from fire and debris (Nicas et al., 2018) and by poor communication and deteriorating fire conditions, which led many to leave at the same time (Todd et al., 2019). Three of the four major evacuation routes out of Paradise caught fire, and some had to abandon their vehicles to escape on foot (St. John et al., 2018). Evacuees from other wildfires including the 2017 December Southern California Wildfires and the 2018 Woolsey Fire also experienced severe congestion, sometimes due to single-exit neighborhoods (Wong et al., 2020), which has been found to be problematic in previous studies (Wolshon and Marchive III, 2007; Cova et al., 2013).

In response to these congestion challenges, a number of transportation response measures and strategies have been developed and implemented in evacuations for a variety of hazards as seen in Table 3 (Lindell et al., 2019). Despite these advances, local, regional, and state agencies still struggle with how to spatially and temporally implement strategies to achieve the highest effectiveness in reducing congestion. Moreover, congestion can have a feedback loop. Survey research found that 10% of evacuees from Hurricane Rita would choose not to evacuate for the next hurricane (Zhang et al., 2007). Struggling to effectively plan and implement evacuations, agencies need empirically driven transportation strategies to better combat congestion.

Table 3: Examples of Transportation Response Strategies for Evacuation Management (adapted from Lindell et al., 2019)

Temporal Strategies	
Timely departures	Encouraging residents to evacuate in a timely manner to reduce last-minute evacuation or rapid loading of the road network

Phased evacuation	Issuing mandatory evacuation orders and releasing evacuees by pre-designated zone to reduce rapid loading of the road network
Supply Strategies	
Contraflow	Switching all or some lanes of a highway or other road to flow away from the hazard to increase roadway capacity
Shoulder usage	Allowing vehicles to drive on the side of a road (typically a highway) to increase roadway capacity
Ramp closures	Closing ramps to highways to reduce bottlenecks and improve travel speeds of vehicles on the highway
Route closures	Closing routes to reduce vehicle movements into the hazardous area or reduce conflict with non-evacuees (e.g., freight)
Turn restrictions	Restricting turning at an intersection to increase flow through the intersection or prioritize evacuating vehicles
Signal priority	Setting traffic signals to prioritize certain traffic movements to increase flow through the intersection or prioritize evacuating vehicles
Manual traffic control	Controlling the flow of traffic through an intersection manually to increase flow through the intersection or prioritize evacuating vehicles
Public Transit	Using high capacity public transit vehicles to reduce the use of single-occupancy vehicles and increase the number of evacuees
Parking restrictions	Restricting parking periodically or permanently along roadways to reduce pinch points and increase flow of vehicles
Informational Strategies	
Route guidance	Providing evacuees with guidance on safe and efficient routes along with dynamic rerouting information to decrease travel times and reduce congestion on highly-traveled roads
System monitoring	Monitoring traffic using intelligent transportation system (ITS) technology to identify accidents and problem areas, determine the effectiveness of responses, and change responses as needed
Travel information	Communicating traffic and service information to evacuees before and during the evacuation to convey shelter locations, alternate evacuation routes, congestion alerts, and location of services

2.2.3) Social Equity

Social equity refers to justice and fairness and has varying definitions depending on the field of study (e.g., social science, public policy), unit of analysis (e.g., individual, group, geography), and type of equity (e.g., outcome, opportunity, access for all, ability to pay). Equity as a concept is often a perceived construct, and many types of equity, particularly for transportation, are mutually exclusive, confounding, or orthogonal in ideology (Taylor, 2004; Transportation Research Board, 2011). For the purposes of this dissertation, social equity is defined as the:

"*active commitment to fairness, justice, and equality in the formulation of public policy, distribution of public services, implementation of public policy, and management of all institutions serving the public directly or by contract. Public administrators, including all persons involved in public governance, should seek to prevent and reduce inequality, unfairness, and injustice based on significant social characteristics and to promote greater equality in access to services, procedural fairness, quality of services, and social outcomes*" (Johnson and Svara, 2015).

This definition of social equity is particularly relevant, as it relates directly to public administration and encompasses larger evacuation goals: access to transportation and sheltering, fair treatment in the communication and evacuation process, quality of life throughout the disaster, and safety from the hazard. In addition, this dissertation focuses on vulnerable populations from a group perspective. Vulnerable groups are classified as groups that may be disadvantaged in a disaster and evacuation due to a lack of resources, access and functional needs (AFN), limited rights, and/or discrimination. A list of some examples of vulnerable groups are provided in Table 4. Additional seminal work on the development of social equity can be found in Rawls (1971), Hart (1974), Leventhal (1980), and Frederickson (2015).

Challenges and barriers in evacuations and disasters have been widely considered and researched, including earlier work related to ethnicity, race, gender, and community vulnerability (Perry and Green, 1982; Fothergill, 1996; Peacock et al., 1997; Morrow, 1999; Fothergill et al., 1999; Fothergill and Peek, 2004). However, Hurricane Katrina in 2005 acutely exposed the lack of social equity in evacuations. Prior to the hurricane, it was estimated that 200,000 to 300,000 of the 1.4 million residents of the New Orleans metropolitan area had little to no access to reliable personal transportation (Wolshon, 2002). An estimated 197,000 people did not evacuate from the storm, over 60,000 had to be rescued from flooding, and over 100,000 had to shelter at refuges of last resort (Boyd et al., 2009). Hurricane Katrina hit low-income, predominately African-American neighborhoods the hardest, due in part to long-standing institutional discrimination (Henkel et al., 2006). The social inequality exposed during Hurricane Katrina for many vulnerable groups has been thoroughly reviewed across multiple fields of study (Hartman and Squires, 2006; Litman, 2006; McDougall, 2007; Renne et al., 2008; Brunkard et al., 2008).

While changes were made in evacuation planning to improve social equity (Post-Katrina Emergency Management Reform Act, 2006; The City of New Orleans, 2019), more recent research has found that just 26% of evacuation plans from the 50 largest U.S. cities described in detail how to assist carless and vulnerable populations (Renne and Mayorga, 2018). Recent hurricanes including Hurricane Irma in Florida, Hurricane Harvey in Texas, and Hurricane Maria in Puerto Rico all severely impacted vulnerable populations (Misra and Walljasper, 2017; Mock, 2017; Allen and Penaloza, 2017) In recent California wildfires, social equity issues became apparent in the communication of mandatory evacuation orders in the face of rapidly spreading fires. Many local agencies had difficulty deciding where and when to issue evacuation orders and how to manage transportation systems due to the speed of the wildfires (Watkins et al., 2017; Lewis et al., 2018; Nicas et al., 2018). The result was that 77% of those who perished in the 2018 Camp Fire were over the age of 65, a group also linked to disabilities and social isolation (Newberry, 2019). During the Getty Fire in 2019, the Los Angeles emergency alert system did not send Spanish notifications at the same time as English alerts (Shyong, 2019). While social equity has slowly gained recognition as a critical challenge in evacuations, significantly more research and planning are necessary to increase fairness in access to and quality of services.

Table 4: Examples of Vulnerable Groups in Evacuations*

Vulnerable Group	Definition
Carless	Do not own a personal vehicle
Low-Income	Under the poverty line based on household size; may also include individuals who do not earn a living wage
Unbanked and Underbanked	Do not have a bank account and/or a credit or debit card
Asset Poor	Have less than $500 in cash assets available for use
Racial and Ethnic Minority	Are not in a dominant position and suffer discrimination based on physical and/or cultural traits
Older Adult	Age 65 and over
Physically Disabled	Physical impairment that substantially limits major life activity
Cognitively Disabled	Learning or intellectual impairment that substantially limits development and/or major life activity
Psychologically Disabled	Psychological impairment that substantially limits major life activity; includes mental conditions
Homebound	Unable to leave home; individuals may also be socially isolated
Assisted Living	Located at a nursing home or other similar types of facilities
Hospital Bound	Located at a hospital due to health reasons; may be permanent or temporary
Immigrant	From a different country and comes to live permanently; may or may not be a citizen
Undocumented Immigrant	From a different country and does not have legal immigration status
Non-Native English Speaker	Speaks a language other than English
LGBTQ+	Gender-based and sexuality-based identity (lesbian/gay/bisexual/transgender/queer/other self-identification)
Homeless	Without an established or regular home
Required Worker	Must work, by law, in disaster events
Child	Under the age of 18
Incarcerated Person	Held or confined in a prison, jail, or other institution to restrict physical movement

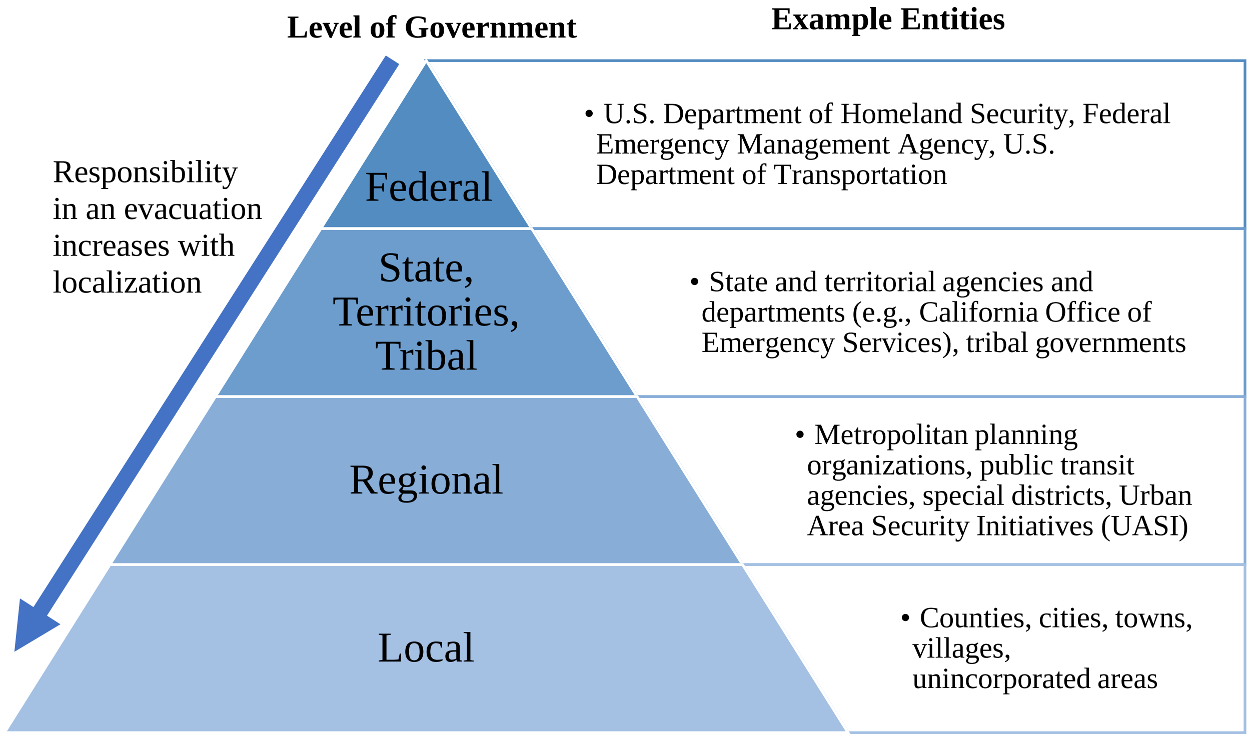
*Note: The term used to describe the vulnerable group, the definition of the vulnerable group, and who is classified as vulnerable will likely change. The table represents the current status of accepted terminology and may not necessarily match future socially accepted language regarding vulnerable populations or social equity.

2.3) Governance Structure

The impact of hazards (both natural and human-made) on communities across the U.S. underscores the need for holistic, evidence-based transportation planning and response strategies that can also be tailored to the unique characteristics of the hazard and community. Disasters and hazardous events *begin and end at the local level*. This common phrase is used to denote how local individuals (e.g., chief elected or appointed officials, emergency managers, local department and agency heads, households, and individuals) are the first to be impacted by an event. The leading role of local government in developing preparedness strategies, responding first to events, and providing long-term relief is outlined in the National Response Framework or NRF (U.S. Department of Homeland Security, 2008). The NRF also outlines how state, territorial and tribal governments are responsible for supplementing and facilitating local efforts. When an incident exceeds state resources or the event involves federal interests (e.g., domestic terrorism), the federal government possesses resources and capabilities to supplement state and local efforts (U.S. Department of Homeland Security, 2008; FEMA, 2010). This structure is important to note, since the federal government offers no or minimal response during an event unless requested by local and state officials. This federal structure was largely developed through the Robert T. Stafford Disaster Relief and Emergency Assistance Act (1988), which gave considerable authority to the President and the Federal Emergency Management Agency (FEMA) in directing mitigation, preparedness, response planning, and allocation of funding. Consequently, evacuation protocols, procedures, and responses are developed and implemented at the local and state levels (Figure 1).

At the local level, a multitude of different entities engage with evacuation orders and transportation, depending on the hazard and geography. For example, evacuation orders are typically issued by city or county emergency management agencies in California, but other entities including special districts, tribal governments, and state agencies may issue orders (California Office of Emergency Services, 2017). In Texas, evacuation orders can be issued by mayors, county judges, and the governor (Texas H.B. No. 1831, 2009). In some cases, regional authorities including metropolitan planning organizations (MPOs) and multi-jurisdictional public transit agencies play key roles in organizing transportation response. For example, in the San Francisco Bay Area, the Metropolitan Transportation Commission (MTC) is the coordinating entity for transportation response, including mass transportation needs, in an evacuation (California Emergency Management Agency, 2011). This complexity in governance structure for evacuation implementation makes it difficult to provide specific recommendations for jurisdictions. In the context of this dissertation, the term *agencies* is used as a catch-all term for local and regional entities that are involved in the planning and implementation of evacuations. This includes entities (e.g., elected offices, departments, public transit districts, other special districts) with jurisdiction in counties, cities, towns, villages, and unincorporated areas. Recommendations are offered for each chapter and summarized in Chapter 10 (Conclusions).

Figure 1: Responsibility in Planning and Implementing Evacuations



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Chapter 3: Bridging the Gap Between Evacuations and the Sharing Economy

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ABSTRACT

This paper examines the opportunities for addressing evacuations by leveraging the sharing economy. To support this research, we use a mixed-method approach employing archival research of sharing economy actions, 24 high-ranking expert interviews, and a survey of individuals impacted by Hurricane Irma in 2017 (n=645). Using these data, we contribute to the literature in four key ways. First, we summarize sharing economy company actions in 30 U.S. disasters. Second, we discuss results from 24 expert interviews on 11 sharing economy benefits (ranging from resource redundancy to positive company press coverage) and 13 limitations (ranging from driver reliability to the digital divide). Experts included six directors/executives of emergency/transportation agencies, two executives of sharing economy companies, and eight senior-level agency leaders. Third, we use these interviews, specifically negative opinions of the sharing economy, to inform our Hurricane Irma survey, which contributes empirical evidence of the feasibility of shared resources. Despite just 1.1% and 5.4% of respondents using transportation network companies (TNCs, also known as ridesourcing and ridehailing) and homesharing respectively during the Irma evacuation, some respondents were extremely willing to offer their own resources including transportation before evacuating (29.1%), transportation while evacuating (23.6%), and shelter for free (19.2%) in a future disaster. We also find spare capacity of private assets exists for future evacuations with just 11.1% and 16% of respondents without spare seatbelts and beds/mattresses, respectively. Finally, we conclude with practice-ready policy recommendations for public agencies to leverage shared resources including: communication partnerships, surge flagging (i.e., identifying and reducing unfair price increases), and community-based sharing systems.

Keywords: evacuations, sharing economy, shared mobility, transportation network company (TNC), Hurricane Irma, emergency management

3.1) Introduction

In the past 20 years, transportation has grown to become an integral part of emergency management. For a variety of hazardous events, evacuations are the primary method to ensure the safety of large populations in the United States (U.S.). While large-scale hurricane evacuations have gained the majority of attention, wildfires in California have also led to the evacuation of hundreds of thousands of residents. At the same time, officials continue to struggle with managing transportation in preparing for, responding to, and recovering from disasters. With the spread of new technological advances, agencies have an opportunity to leverage new ideas to increase evacuation compliance rates, reduce congestion, support vulnerable populations, and ensure resident safety (Wong et al., 2018a; Li et al., 2018). One key advance has been the development of the sharing economy, an Internet-based collection of company-to-peer and peer-to-peer transactions where goods and services are shared and obtained. Companies, including Airbnb, Lyft, Uber, Turo, and Getaround, have disrupted traditional economic and service structures, gaining immense popularity. This online "collaborative consumption" has grown with the help of information and communications technology (ICT), consumer awareness, and sharing economy "companies," rather than just online communities (Hamari et al., 2016). With the proliferation of smartphone technology, consumers are able to access resources through the sharing economy rapidly and efficiently. The explosive growth of these companies has also exposed them to external forces in the marketplace, including disasters. The size and reach of some sharing economy companies suggest that their presence (or lack thereof) in disasters could impact transportation and sheltering operations in communities (Wong et al., 2018a). Research on the application of the sharing economy to disaster response and relief is needed to better assess its feasibility.

To bridge the gap between evacuations and the sharing economy, we employ a mixed-method approach composed of archival research, expert interviews (n=24), and a survey of impacted individuals from Hurricane Irma (n=645). We begin by presenting relevant literature on evacuation behavior and logistics followed by methodology. Next, we summarize the actions of sharing economy companies in 30 disasters. These disasters include large-scale events (involving the evacuation of thousands and millions, such as large hurricanes and wildfires) and small-scale events (leading to only localized impacts with lower evacuation needs such as: small floods, snow storms, and shootings). Given the widespread actions of companies across disasters, we formulated an interview guide to elicit opinions from experts on the benefits and limitations of a shared resource strategy. We present these expert interview findings on use cases, benefits, and limitations. Expert concerns over the potential lack of capacity and willingness to provide resources informed our survey questions, focusing our attention on exploring providers' willingness to share. We next present the survey results on shared resources. Finally, we conclude with policy recommendations to build a framework for shared resources in disasters.

3.2) Literature on Evacuation Behavior and Logistics

In this section, we provide background on evacuation behavior, logistics of mode and shelter demand, and literature gaps. We blend the literature of evacuation behavior and logistics to highlight demand for key evacuation resources and provide context for the sharing economy strategy, which aims to better match evacuation resource demand and supply.

3.2.1) Evacuation Behavior

For evacuations, individuals must make a number of critical decisions (to evacuate or stay, departure time, transportation mode, route, destination, shelter type, reentry time). These choices have important impacts on evacuation response and outcomes. For example, the number of individuals who decide to evacuate affects the transportation system and may require supply-side strategies, such as contraflow (reversing lanes to all flow away from a hazard) to manage demand. Research on evacuation behavior has been predominately spurred by the devastating impacts of disasters. Some of the earliest research focused on how individuals received evacuation orders for the Big Thompson Flood and their subsequent actions (Gruntfest, 1977). The Three Mile Island Accident in 1979 also drove research into evacuation behavior and risk perception. Cutter and Barnes (1982) found that individuals experienced significant confusion about the hazard and evacuation process. The lack of information (along with social influence) led more people to evacuate than was expected, overloading roads. Following Three Mile Island, research in the field also focused on the development of evacuation time estimates (ETEs) (Lindell and Perry, 1992; Urbanik, 1994). These time estimates remain the primary metric for evacuation modeling, as they indicate when a population has been safely evacuated. ETEs are also heavily influenced by evacuee behavior. For example, if households take multiple vehicles, ETEs will rise and can impact transportation response. Lindell and Prater (2007) provide a comprehensive review of behavioral assumptions that must be made for ETEs, especially as they relate to evacuation modeling. Early work also has been instrumental in summarizing evacuee behavior. Perry et al. (1981) compared the evacuation decision-making process between nuclear and nonnuclear threats, finding that those who chose not to evacuate did not believe they were in danger. Along with Perry et al. (1981), multiple studies have also focused on how evacuees receive information and what they decide to do with it (see Drabek, 1986; Sorensen et al., 1987; Sorensen, 1991; Drabek, 1999; Sorensen, 2000 for overviews).

Notable advances in hurricane evacuation literature have included choice making and logistics analysis (Urbanik, 1979; Baker, 1979; Baker, 1990; Baker, 1991; Gladwin, 1997; Dow and Cutter, 1998; Baker, 2000). Baker (1990) and Gladwin (1997) found a lack of compliance in evacuation zones (geographic areas given evacuation orders) and an increase in shadow evacuations (large evacuations by households without evacuation orders) to be problematic in hurricane evacuations. While low compliance indicates an obvious safety issue, shadow evacuations (along with background traffic) are also safety issues because they significantly increase demand and ETEs. This is because congestion from shadow evacuations and background traffic can propagate into evacuation zones, increasing the risk that evacuees will be impacted by the hazard. Baker (1991) summarized the state of evacuation behavior research by assessing twelve hurricanes. This study found that a number of variables impacted evacuation behavior including: 1) risk level, 2) action by public authorities, 3) housing (current residence), 4) risk perception, and 5) hurricane-specific factors (e.g., category, storm surge predictions). Baker (1991) also found demographics to be poor predictors of evacuation behavior, but social cues (e.g., neighbors) were influential. Dow and Cutter (1998) focused on decisions in multiple evacuation events, particularly the influence of false alarms. Repeated false alarms were hypothesized to decrease future evacuation rates, but Dow and Cutter (1998) found the "crying wolf" impact was negligible.

In 1999, Hurricane Floyd led to the evacuation of 2.5 million people, exposing the inability of emergency plans and transportation systems to adequately move large populations. Some of the first large-scale attempts at contraflow were instituted for Floyd, but the capacity improvements were tempered by issues of safety, in-bound accessibility, and cost (Wolshon, 2001). The public outcry over the Floyd traffic jams led to increased involvement of state transportation departments and transportation professionals. State and local plans were reworked to include new evacuation strategies (Urbina and Wolshon, 2003; Wolshon et al., 2005). While many of these strategies were focused on increasing capacity along roadways and assessing evacuee behavior, several included increasing involvement of the transportation engineering community in emergency planning and developing interstate cooperation to support transportation management.

Evacuation behavior analysis has continued to evolve dramatically by employing rigorous methods to determine the influencers of choice. Many of these studies have employed statistical methods, such as discrete choice modeling to analyze decision-making in disasters (see Wong et al., 2018b for a review). While most studies have focused on the decision to evacuate or not (Hasan et al., 2011; Huang et al., 2012; Murray-Tuite et al., 2012), other papers address additional aspects of evacuee decisions. Key examples include departure timing (Fu and Wilmot, 2004; Fu et al., 2006); shelter type (Mesa-Arango et al., 2013); route (Sadri et al., 2014a; Sadri et al., 2015); and transportation mode (Sadri et al., 2014b).

For logistics, shelter type and transportation mode are two primary choices that have broad impacts on evacuation outcomes. In Sadri et al. (2014b), respondents without vehicle access were given a hypothetical hurricane scenario to make a modal decision. In addition to assessing the factors that impact mode choice (in particular income, household size, age, and shelter), the study found that 41% would ride with someone from another household, about 34% would take an evacuation bus or regular bus, and 8% would take a taxi. Deka and Carnegie (2010) also assessed transportation mode decisions, finding that mode split in the community and vehicle ownership were key factors along with some demographic characteristics including: education, age, race, marital status, and having an individual with a disability in the household. Wong et al. (2018b) also found vehicle ownership to be significant, along with stronger impacts of destination and weaker influence of income, age, and length of residence. For shelter type, Mesa-Arango et al. (2013) found work requirements, mandatory evacuation orders, income, and variables associated with the final destination impacted shelter decision-making. Other shelter choice studies, including Whitehead (2000), Smith and McCarty (2009), and Deka and Carnegie (2010), found the presence of demographics influencing shelter choice such as: age, homeownership, marital status, race, income, length of residence, and household size. These behavioral studies have played a key role in developing more accurate evacuation models that predict traffic patterns and bolster data-driven preparedness strategies. Similar to Mesa-Arango et al. (2013), Wong et al. (2018b) found that destination was highly correlated with shelter choice. The study also found weak impacts from risk perceptions and age, but some correlation with length of residence, pets in the household, and income.

3.2.2) Evacuation Logistics - Mode and Shelter Demand

While understanding the factors that impact choice are critical, assessing the modal and shelter type split is also useful for determining evacuee demand. For mode, the number of evacuating vehicles – or demand – is a critical metric that impacts evacuation response and outcomes. Naturally, road network capacity and the number of possible evacuation routes (supply) constrain the number of evacuating vehicles. Lindell et al. (2019) provides an in-depth review of the interplay between supply and demand. For most hurricane evacuations, research has found that evacuees almost always use their own private vehicles to evacuate (Table 1). Consistent results across hurricanes, including Hurricanes Bret, Lili, Katrina, Rita, Ike, and Irma, indicate that private vehicles account for 87% to 96% of evacuee modal choice (Prater et al., 2000; Lindell et al., 2011; Wu et al., 2012; Wu et al., 2013; Wilmot and Gudishala, 2013; Wong et al., 2018b). As seen in Table 1, carpooling or receiving a ride from someone else accounts for 2% to 10% of the modal split. Public transit use is low, hovering around 1% across studies, while other modes represent 0% to 7% of mode choice. A number of these studies have also calculated the number of vehicles per household that evacuate, which tends to vary substantially. Households choose to evacuate with multiple vehicles for a variety of reasons, beyond ensuring that every household member has a seat. Evacuees may want to take additional luggage, protect their vehicles, or have great flexibility in travel near their destination. Some studies, including Wu et al. (2013), calculated the percent of registered vehicles used in an evacuation. In this case, 62% of registered vehicles were used for Hurricane Ike. Using correlation tables, several studies found factors that correlated with modal choice and taking additional vehicles (Dow and Cutter, 2002; Lindell et al., 2011; Wu et al., 2013; Yin et al., 2014). This research is summarized in Lindell et al. (2019), along with some additional work on the relevance of trailers on roadways for impacting vehicle demand.

Table 1: Transportation Mode by Disaster (adapted from Lindell et al., 2019)

Author(s) (Year)	Hurricane (Year)	Sample Size (Survey Distribution)	Own Vehicle	Received Ride	Public Transit	Other	# of Evacuating Vehicles
Prater et al. (2000)	Hurricane Bret (1999)	79 (mail)	88%	7%	1%	4%	1.34
Lindell et al. (2011)	Hurricane Lili (2002)	263 (mail)	90%	9%	1%	0%	1.10 to 2.15
Wu et al. (2012)	Hurricanes Katrina/Rita (2005)	1056 (mail)	89%	8%	<1%	3%	1.42
Wilmot and Gudishala (2013)	Hurricane Gustav (2008)	300 (mail)	96%	3%	1%	<1%	NA
Wu et al. (2013)	Hurricane Ike (2008)	346 (mail)	87%	10%	1%	2%	1.25
Wong et al. (2018b)	Hurricane Irma (2017)	368 (online)	90%	2%	1%	7%	NA

Similar to mode choice, shelter choice split assesses evacuee demand for public resources, especially public shelters. As seen in Table 2 below, most evacuees have sheltered with friends and family, ranging from 44% to 70%. Public shelter usage was far lower, between 2% and 11%. While these percentages may indicate minimal need, applying a 5% public shelter usage rate across an evacuating population of 1 million would require 50,000 beds. Hotels and motels tend to be used highly, with a range of 16% to 46%. A number of shelters were also classified as "other," which includes second residences, recreational vehicles, places of work, and private vehicles. One important note is that Wong et al. (2018b) found that 5% of evacuees sheltered using a peer-to-peer sharing economy service (such as Airbnb). This result points to a potential for the sharing economy as a sheltering strategy, which is addressed in the next section.

Table 2: Shelter Type for Recent Hurricanes (adapted from Lindell et al., 2019)

Author(s) (Year)	Disaster (Year)	Sample Size (Survey Distribution)	Friends and Family	Public Shelters	Hotels/ Motels	Other
Prater et al. (2000)	Hurricane Bret (1999)	82 (mail)	62%	3%	27%	9%
Whitehead (2003)	Hurricane Bonnie (1998)	235 (telephone)	70%	6%	16%	9%
Smith and McCarty (2009)	Hurricane Charley Hurricane Frances Hurricane Ivan Hurricane Jeanne (2004)	11,559 (telephone)	57% to 65%	3% to 11%	7% to 25%	13% to 18%
Cheng et al. (2011)	Hurricane Floyd (1999)	1136 (telephone)	60%	4%	32%	5%
Lindell et al. (2011)	Hurricane Lili (2002)	263 (mail)	54%	3%	29%	14%
Wu et al. (2012)	Hurricane Katrina/Rita (2005)	1028 (mail)	61%	3%	18%	18%
Wilmot and Gudishala (2013)	Hurricane Gustav (2008)	300 (mail)	44%	2%	46%	8%
Wu et al. (2013)	Hurricane Ike (2008)	338 (mail)	63%	2%	30%	5%
Yin et al. (2014)	Hurricane Ivan (2004)	853 (telephone)	62%	2%	22%	14%
Wong et al. (2018b)	Hurricane Irma (2017)	368 (online)	59%	4%	27%	10%*

* Approximately 5% of evacuees used a peer-to-peer service such as Airbnb for sheltering

Finally, while many previous disasters have led to significant congestion on roadways due to limited road network capacity, Hurricane Katrina in 2005 most acutely displayed the impacts of a lack of transportation and sheltering availability. Prior to Hurricane Katrina, the New Orleans evacuation plan did not include a process for providing transportation for carless residents (Wolshon, 2002; Renne, 2006). Wolshon (2002) predicted that upward of 200,000 to 300,000 did not have access to personal transportation. Katrina led to a renewed effort to identify lessons learned and create extensive recommendations for various levels of governance (Litman, 2006; Renne et al., 2008). Very soon after Katrina, officials issued a massive mandatory evacuation for Hurricane Rita, causing severe congestion, fuel and emergency supply shortages, and leading some to turn back home. Afterward, professionals and planners refined demand prediction models along certain routes, developed new models for shadow evacuations, and began to look into addressing the need for services along highways (Murray-Tuite and Wolshon, 2013). Other studies have also offered recommendations for vulnerable populations including ideas for transporting older populations (Gibson and Hayunga, 2006); aiding carless and special needs populations (Renne et al., 2011); and helping independent living individuals who are older and/or disabled (Cahalan and Renne, 2007). Recent work has focused on building more robust and equitable evacuations by leveraging public transit strategies (Bish, 2011) and optimizing transit pickup locations for vulnerable groups (Bian and Wilmot, 2017). Despite this equity push, research has found that one-third of the 50 largest cities in the US do not have evacuation plans (Renne and Mayorga, 2018). This research also found that less than half of cities with evacuation plans mention carless or vulnerable populations. Even for the relatively successful Hurricane Irma evacuations, issues with evacuating nursing homes, hospitals, and carless populations were widespread (Bliss, 2017). Hurricane Maria, which devastated Puerto Rico in 2017, caused significant damage across the island to its transportation system (Lazo, 2017) and electricity grid (Federal Emergency Management Agency 2018), forcing many to seek housing in inadequate public shelters (Allen and Penaloza, 2017). In an after-action report, the Federal Emergency Management Agency (FEMA) acknowledged that the agency did not anticipate the widespread damage that Maria would cause to Puerto Rico (Federal Emergency Management Agency, 2018). The report recommended increasing transportation planning and management capacities and building a stronger relationship with private-sector partners to recover more quickly. Finally, the report noted the crucial role of volunteers, non-profit organizations, and the private sector across the 2017 hurricane season for providing transportation and sheltering (Federal Emergency Management Agency, 2018).

3.2.3) Key Literature Gaps

As evidenced throughout this review, several key gaps in the literature emerge. First, much of the research has focused on the vehicle demand but not on strategies for increasing transportation supply. While most individuals continue to use private vehicles, a significant proportion of people continue to rely on carpooling, public transit, and other modes. Moreover, modal split statistics fail to capture the number of people who did not evacuate because they did not have access to transportation. Indeed, carless households in the US continue to comprise a large proportion of at-risk cities for hurricanes such as: Houston (8.6%), Charleston (7.6%), Tampa (10.9%), Miami (19.8%), and New Orleans (19.2%) (U.S. Census Bureau, 2018). In Houston alone, 8.6% of carless household would equate to over 70,000 *households* that would have no access to a private vehicle in the event of an evacuation. Moreover, even some individuals with private vehicles may be unable to transport themselves. This might include individuals with disabilities, older adults, or people without immediate vehicle access (e.g., vehicle in repair).

Second, the majority of logistic studies continue to focus on shelter type split without addressing the high need for free sheltering options through public shelters. Moreover, it remains unclear how many people decide to forgo evacuating because they do not have adequate shelter. Wong et al. (2018b) found that 31% of non-evacuees stated that one reason they did not evacuate was because they did not want to go to a public shelter. At the same time, 14% said that they did not have enough money to evacuate. Evacuees often view public shelters as a last resort, and some cannot afford to travel far distances to friends and family or pay for a hotel. Increasing sheltering supply, especially supply that is considered adequate and comfortable, may help increase compliance rates and alter evacuee behavior.

Finally, ad hoc resources for evacuations remain an understudied research area. While some work has been conducted on public shelter, public transit, and carpooling logistics, little research has considered the role of the sharing economy. This is especially relevant given the ease of emerging technologies and communication that could facilitate matching supply and demand in evacuations. Moreover, some planning guidelines encourage consideration of all available and accessible transportation resources into evacuation plans (Federal Emergency Management Agency, 2010). State emergency plans, for example in Texas, note that large-scale events may require additional transportation resources beyond public ones, and volunteer assistance (either planned or spontaneous) may be required in these events (State of Texas, 2016). The California Emergency

Plan also recognizes the role of private entities through the creation of the Business Operations Center, which is housed in the logistics section of the state operation center (Cal OES, 2016). With these needs and policy mechanisms already in place, the sharing economy could play a strategic role in filling unused capacity in vehicles and shelters and improve evacuation outcomes.

3.3) Research Questions and Contributions

The goal of this paper is to bridge the gap between two distinct research tracks: evacuations and the sharing economy. To our knowledge, no research paper has compiled sharing economy actions during disasters or assessed the willingness of individuals to provide their own resources in a disaster via the sharing economy. While the idea of shared resources has been described before (Wong et al., 2018a) and assessed in a Chinese context (Li et al., 2018), this paper is the only U.S. study to investigate the application and potential of the broader sharing economy in evacuations. More specifically, we offer archival evidence of past sharing economy actions, expert opinions on shared resource benefits and limitations, and empirical evidence from individuals recently impacted by a disaster on their willingness to provide resources. While Li et al. (2018) also interviewed experts on benefits and limitations, the paper surveyed carless individuals, not individuals impacted by a disaster, which helped assess sharing demand. In our paper, we focus on the capacity of shared resources, which is a prerequisite for implementing a shared resource strategy for evacuations. To guide this study, we formulated several research questions:

(1) What is the role of the sharing economy in disasters?
(2) What are the benefits and limitations of public-private partnerships that involve the sharing economy?
(3) What is the magnitude of spare capacity in vehicles or houses to evacuate and shelter?
(4) Are individuals willing to provide rides or shelter for evacuees?

These four research questions each contribute to the overall assessment of the sharing economy in evacuations. With the first question providing background on the sharing economy, the second question begins to address the feasibility and theoretical framework of the sharing economy in disasters through qualitative data gathering. While qualitative data develops the framework, empirical evidence helps answer questions three and four, which finds a quantitative capacity for the sharing economy. Together, the four questions theoretically and empirically explore the sharing economy strategy for evacuations and provide a starting point for future work in the field.

3.4) Methodology

To answer the research questions, we employed a mixed-method approach to bring together evacuation and sharing economy research. Addressing the first research question, we first conducted a comprehensive archival review of current sharing economy company actions in 30 U.S. disasters. This review provides context for the current role of the sharing economy in evacuations and informed our expert interviews. Next, we conducted a series of high-ranking expert interviews between February and April 2017 to answer the second research question. We developed a list of potential experts based on several factors including:

1) Experience and knowledge in developing or implementing transportation management policies, procedures, or protocols for disaster situations;
2) High-ranking leaders and/or senior officials with authority in disaster situations;

3) Geographic diversity in areas that traditionally experience natural disasters including the West Coast (earthquakes and wildfires), Gulf Coast and South (hurricanes), East Coast (hurricanes and winter storms), and Midwest (tornadoes); and
4) Employment diversity in different fields related to emergency management.

Using these criteria, we compiled a list of U.S. experts. We asked each to participate in an interview via email and to also identify other evacuation experts. We employed this snowball sampling technique to increase the interview pool and leverage the persuasive influence of a referral system. Expert interviews averaged about one hour and were completed with 24 experts. This method was intended to increase the diversity of answers and opinions (Weiss, 1995). Near the end of the interviewing process, a number of answers provided were duplicates of past interviews; this suggested a saturation of usable information and led the team to end with 24 interviews. More importantly, the 24 interviews successfully answered the research questions.

While experts offered high-level opinions of the sharing economy, full implementation of a sharing economy strategy requires that evacuees and non-evacuees have the willingness and capacity to share resources. Experts were highly concerned about the feasibility of the sharing economy, explaining that people may not want to share in a disaster. Specifically, they were concerned that drivers may be unwilling to provide transportation and that a number of reservations (e.g., concerns about safety and security, worry about interacting with a stranger) would severely limit the sharing economy strategy. Moreover, several experts asserted that only a small number of individuals would provide services and it would be inadequate for community needs. Given these negative expert opinions, we crafted a survey addressing sharing capacity, willingness to share, and potential reasons against sharing. In contrast to Li et al. (2018), which surveyed a general population without disaster experience, we distributed the online survey to individuals impacted by Hurricane Irma in 2017 between October and December 2017 across the state of Florida. The survey offers empirical evidence to answer the third and fourth research questions.

Hurricane Irma, one of the most powerful hurricanes ever recorded, led to one of the largest evacuations in U.S. history with over six million people, mostly in Florida, ordered to evacuate. Even though Irma weakened significantly after making landfall, the storm resulted in an estimated $50 billion in damages and 92 deaths in the U.S. (National Oceanic and Atmospheric Administration, 2018). Considering the large size of Hurricane Irma and the wide-spread evacuations, we posted the survey online to various locations including: Facebook, Twitter, online websites, and alert subscription services with the help of local emergency management, transportation, public transit, and planning agencies. These agencies were selected based on the population size of their jurisdiction and their proximity to Hurricane Irma. Respondents were incentivized with the opportunity to win one of five $200 gift cards. The survey yielded 1,266 responses, 938 completed surveys (74% completion rate) and 645 final responses after intensive data cleaning for analysis.

3.5) Archival Results and Discussion

Recently, the ubiquitousness of the Internet and social media has ushered in new strategies for emergencies, opening new doors for dissemination, resource access, and data collection for transportation emergency management. The catalyzing event for this switch towards Internet-based strategies was Hurricane Sandy in 2012, one the most severe disasters in the U.S. since the beginning of mass consumption of social media and smartphone technology. New York City Transit used Twitter to provide updates about the storm, subway service, closures, false reports, and recovery efforts (Chan and Schofer, 2014). For other services – such as fire and police – agency websites, Twitter, Facebook, and Nixle were used for communicating messages regarding the storm for some departments (Hughes et al., 2014). For federal agencies, social media was used across different platforms for a variety of purposes (Department of Homeland Security, 2013). Recent research has used Twitter data to determine user activities across time and space during Hurricane Sandy (Sadri, 2016), identify storm-phase patterns of communication (Sadri et al., 2018), gauge evacuation compliance (Martin et al., 2017), and follow the progression of perceiving and responding to evolving risks (Demuth et al., 2018).

Despite this increase in media consumption via the Internet, evacuees continue to receive information via traditional media forms such as: television, radio, and telephone. For example, Wong et al. (2018b) found that of those who received a mandatory evacuation order for Hurricane Irma, 56% obtained it via a television announcement, 30% through telephone, and 19% through radio. About 48% received the order through social media and 33% via an Internet website. The results indicate that individuals received the order through a number of sources, which confirms previous research on social milling where people seek warning confirmation from other sources (Lindell, 2018). However, social media and Internet use was likely inflated due to the high technology usage of the survey sample. For a boil water order in Boston, Lindell et al. (2017) found that 66% of respondents learned about this order in Boston via television. In the same study, 34% received information via the Internet, 25% through telephone, 21% radio, and just 3% via social media. Lindell et al. (2017) also found that people depend on multiple sources (approximately 1.76 additional channels). Other research has found that individual rely on a number of information sources with just 25% depending on social media during Hurricane Sandy for information (Sadri et al., 2017). At the same time, not all individuals have access to smartphone technology. Recent research has found that 23% of Americans do not own a smartphone (Pew Research Center, 2018a), and 11% do not have broadband Internet access (Pew Research Center, 2018b) Despite these limitations on social media notifications and the clear need to continue using multiple methods of communication in disasters, the spread of smartphone technology has allowed information to move more rapidly through Internet-based media. Moreover, emerging technological capabilities have instigated the rise of the sharing economy in emergency situations as an evacuation strategy. Generally, the sharing economy is coordinated online and allows for obtaining, sharing, and accessing goods and services from peers or businesses.

Transportation network companies (TNCs, also known as ridesourcing and ridehailing), such as Lyft and Uber, allow users to request car rides through a smartphone application and charge riders based on distance and travel time (Rayle et al., 2016). To encourage market equilibrium when demand is high and driver availability is low, TNCs raise prices through a mechanism called primetime or surge pricing. Immediately following Hurricane Sandy, Uber instituted a surge of twice the base price to meet the increase in demand. It received intense criticism on social media by users who saw the move as an unethical method to price gouge customers during an emergency (Walk, 2012; Weiner, 2014), leading Uber to give 100% of proceeds from rides directly to the driver. Another sharing economy platform, Airbnb (a marketplace of homes and rooms where people have the opportunity to rent their space or another's space in hundreds of countries known as homesharing) and its renters displayed the positive benefits of sharing economy networks. In a peer-created movement, nearly 400 Airbnb renters offered their apartments and houses free of charge to anyone in need of housing after Hurricane Sandy (Airbnb, 2017a). The positivity and success of ad hoc homesharing during Sandy led Airbnb to create the Disaster Response Program (now called Open Homes). This program provides alerts to Airbnb renters near disaster areas and encourages them to provide their house free of charge to victims by waiving all fees (Airbnb, 2018a). The sharing economy has acted in 30 disasters in the U.S. since 2012, including Hurricane Sandy (Table 3).

The policy decisions of sharing economy companies during emergency situations have continued to evolve in the U.S., as noted in Table 3. The table reflects a clear progression that sharing economy companies are increasing their presence in emergency events. Airbnb has maintained a consistent protocol for large disasters, opting to use its Disaster Response Tool (Open Homes) and waiving all fees for transactions to help evacuees. Actions by Lyft and Uber have been more sporadic and dependent on geographical offices. More recently, a number of devastating disasters in 2017 and 2018 have revealed additional actions by sharing economy companies that are more extensive, structured, and visible in the public eye. In particular, Hurricanes Harvey and Irma and the wildfires in the North San Francisco Bay Area and Southern California required large evacuations and displaced thousands of people. As seen in Table 3, Lyft and Uber focused their support on offering free and discounted rides to and from evacuation centers and hospitals. Along with guaranteeing monetary contributions, Uber also delivered free meals to first responders during the Southern California fires and began to focus their services toward carless individuals (with an emphasis on older adults) during Hurricane Irma and the North San Francisco Bay fires. Lyft also pledged monetary donations through its Round Up and Donate program. In addition, Lyft pushed its concierge service to reach individuals without smartphones during Hurricane Irma and suspended its Primetime pricing during the Las Vegas shootings. For most of the disasters, Airbnb ran its Open Homes program and received a high number of willing hosts for Hurricanes Harvey (~700), the North Bay wildfires (~900), Hurricane Florence (~600), Hurricane Michael (~1000), the Camp Fire (~2000), and the Woolsey Fire (~1600). While it remains unclear how many people used Airbnb, Uber, and Lyft in these disasters, the improved communication and clear switch toward free relief are indications that these sharing economy companies intend to play key roles in disasters. Additional details and descriptions of sharing economy company actions can be found in Figure A1 in the appendix.

It should also be noted that many sharing economy companies – including Airbnb, Lyft, and Uber – operate internationally. While this paper focuses on U.S. disasters, multiple disasters in recent years around the world have also prompted the support of these companies. Airbnb continues to implement its Open Homes program for not just international disasters but also for housing refugees. While Lyft's operations have only recently expanded to Canada, Uber operates in numerous countries. The two most notable international actions of Uber in emergencies were during the Sydney Hostage Crisis in 2014 – when Uber prices surged but received considerable public backlash (BBC, 2014) – and the Manchester Bombings in 2017 during which Uber provided free rides to safety for concert goers into the morning (Marinova, 2017).

Table 3: Summary of Sharing Economy Actions Across 30 Disasters

	Airbnb	Lyft	Uber
Years Active in Disasters	2012 to present	2015 to present	2012 to present
Disaster Cases with Sharing Economy Actions			
Hurricanes	Sandy (2012) Matthew (2016) Harvey (2017) Irma (2017) Florence (2018) Michael (2018)	Matthew (2016) Harvey (2017) Irma (2017) Florence (2018) Michael (2018)	Sandy (2012) Matthew (2016) Harvey (2017) Irma (2017) Florence (2018) Michael (2018)
Wildfires	Northern California (2017) Southern California (2017) Mendocino Complex (2018) Carr (2018) Camp (2018) Woolsey (2018)	Northern California (2017) Southern California (2017) Carr (2018) Camp (2018) Woolsey (2018)	Northern California (2017) Southern California (2017) Woolsey (2018)
Floods	Houston (2015) Louisiana (2015) Central Texas (2018) Tennessee (2019) March Midwestern U.S. (2019) May Midwestern U.S. (2019)	Austin (2015) March Midwestern U.S. (2019)	Houston (2015) Austin (2015) Missouri and Illinois (2015) March Midwestern U.S. (2019)
Snow Storms	None	Juno (2015)	Nemo (2013) Electra (2013) Juno (2015) Linus (2015)
Tornadoes	Lee County Tornadoes (2019)	None	Texas Tornadoes (2015)
Other	Oroville Dam Crisis (2017) Las Vegas Shootings (2017) Kilauea Volcano (2018)	Las Vegas Shootings (2017)	Las Vegas Shootings (2017) Montecito Mudslides (2018) Kilauea Volcano (2018)
Summary of Sharing Economy Actions			
	2012 to 2013	**2015 to 2016**	**2012 to 2015**
Early Actions (Ad hoc approaches)	• Offered homes free of charge to Hurricane Sandy evacuees in a peer-led movement	• Capped Prime Time surge pricing across early disasters • Suspended service during the disaster	• Increased trip prices (surged) across hurricanes and winter storms and worked to cap surges • Employed UberRELIEF Program on a case-by-case basis, which allowed riders to donate to a disaster relief organization (e.g., American Red Cross)

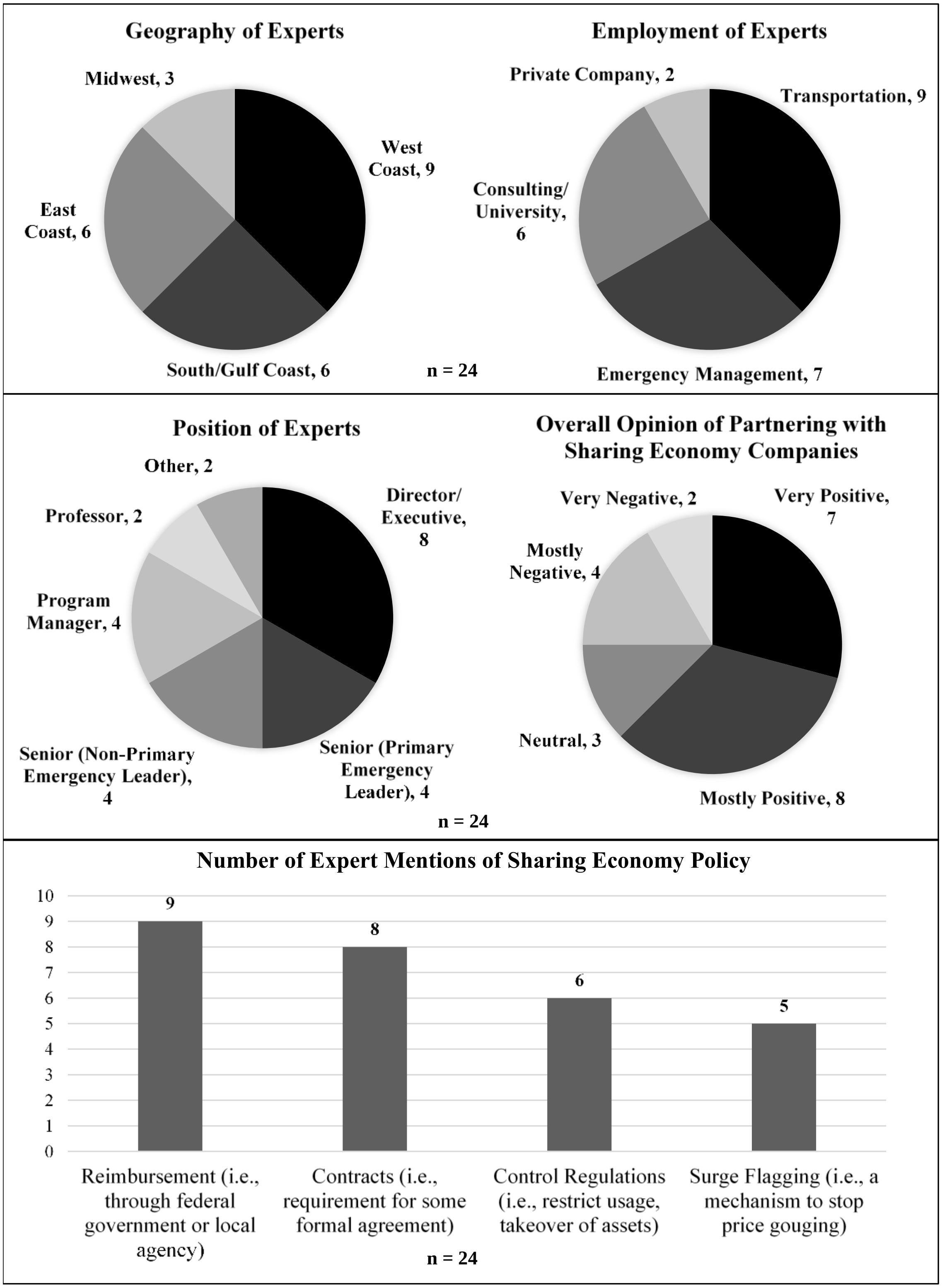
	2014 to 2016	2017	2016 to 2017
Intermediate Actions (Semi-structured approaches)	• Developed Disaster Response Program, which allowed hosts to provide their homes for free on the Airbnb website • Created Memoranda of Understanding with cities to offer housing to disaster relief and share information	• Developed Round Up and Donate Program that allowed users to round up the cost of their trip to the nearest dollar and donate toward a charity, including the United Way for disaster relief • Developed Relief Rides Program, which organizes rides for disaster relief • Offered ride credits to and from evacuation centers	• Offered ride credits to and from evacuation centers following some disasters • Altered the value of credits on a case-by-case basis • Pledged specific dollar amounts for rides, food, and relief for each disaster
	2017 to present	**2018 to present**	**2018 to present**
Current Actions (Highly structured approaches)	• Rebranded Disaster Response Program as the Open Homes Program to include refugee housing • Continues to expand and currently deploys the Open Homes Program following most major disasters, including international disasters • Deploys Open Homes Program for rural disasters	• Rebranded Relief Rides Program as Wheels for All Program, which expanded ride credits to disadvantaged individuals • Partners with a number of organizations including the American Red Cross, Team Rubicon, and United Way • Acts in most disasters where the company operates • Continues to offer ride credits to and from evacuation centers and sometimes hospitals	• Developed the Global Security Center, which now handles most disaster actions of the company • Continues to pledge specific dollar amounts for rides, food, and relief for each disaster • Continues to offer ride credits to and from evacuation centers and sometimes hospitals

As sharing economy companies have grown in the U.S., public-private partnerships have also increased for disasters. In partnerships with cities, including San Francisco and Seattle, Airbnb has pledged to initiate their resources to increase the amount of housing for displaced residents and service workers and pass on critical information to hosts (Airbnb, 2019e). The notable surge prices during Winter Storm Electra in 2013 led to an agreement between Uber and New York State, capping Uber surge pricing during emergencies. The agreement prompted Uber to adopt these standards as a national policy (New York State Office of the Attorney General, 2014). More recently, Uber has taken the initiative to begin tracking incidents and managing operations through its Global Security Center, signaling its push to reconstruct its disaster policy (Hawkins, 2018). Lyft has also more concretely defined its disaster response program – Lyft Relief Rides – for recent disasters, while Airbnb rebranded its disaster policy program as Open Homes.

3.6) Expert Interview Results and Discussion

To develop a richer understanding of the future of sharing economy companies in disasters, we conducted 24 expert interviews between February and April 2017. Experts in disaster response were asked a range of questions regarding their opinions on the sharing economy and associated disaster use cases, benefits, and drawbacks. An overview of expert characteristics and their opinions on several topics are found in Figure 1 below.

Figure 1: Overview of Expert Characteristics and Opinions



3.6.1) Possible Sharing Economy Use Cases

We first asked experts about the potential use cases for the sharing economy in disasters. Answers were subsequently grouped into three separate categories: events, transportation benefits, and non-transportation benefits, and they are presented in Table 4 below. For events, experts noted that the sharing economy could be used for no-notice events (e.g., terrorist attacks, wildfires) or small-scale events (e.g., limited impact or small evacuation disasters) where adaptable resources would be beneficial. Events in dense, downtown locations could use sharing economy resources due to their established presence in major cities. However, experts were not as optimistic about large-scale disasters (e.g., hurricanes, earthquakes), as all people would be affected (including drivers and hosts) and more vehicles on the roadway could lead to congestion. For a direct response, experts suggested that pickups at individual homes would increase accessibility. Direct pickups could specifically assist vulnerable populations, while connections to public transit would increase the use of high-capacity transportation modes. For an indirect response, experts suggested focusing on communication. Sharing economy platforms, particularly on smartphones, could serve as a communication tool for connecting with drivers and passengers through push notifications or within-app notifications.

Table 4: Key Sharing Economy Use Cases Noted by Experts (n=24)

Events *Hazard types and situations*	**Transportation Benefits** *Direct transport response*	**Non-Transportation Benefits** *Indirect transport/housing response*
No-notice events (e.g., wildfires, terrorist attacks)	Pickups at individuals' homes and drop-offs at evacuation centers	Situational awareness of on the ground events
Small-scale disasters (e.g., disasters with localized impacts)	Re-entry to impacted areas	Communication with drivers or passengers of current dangers
Disasters in dense, downtown locations	First-mile, last-mile connections to public transit	Data gathering of behavior during disasters
Some large-scale disasters (e.g., hurricanes) due to size and disaster scope	Rides for vulnerable populations (e.g., carless, older adults) including supplementing paratransit resources	Accommodations for those who need it and methods to train residents

3.6.2) Sharing Economy Benefits

Next, we asked experts about their opinion of sharing economy benefits and how it might help private sharing economy companies and local governmental agencies. Emergency management and transportation agencies stand to gain considerably from partnerships, especially related to resource availability. Private sharing economy companies could benefit in areas of market and customer growth. Table 5 below presents various benefits mentioned by experts.

Table 5: Key Sharing Economy Benefits by Experts (n=24)

Local Governmental Agencies	Sharing Economy Companies
Added resources to move or shelter individuals (supplementing public resources)	Positive press coverage (strengthening media presence to gain more customers)
Redundant resources (ensuring extra resources)	Improved business continuity (helping the community return to normal operations)
More flexible and adaptive resource pool (activating resources quickly)	Asset removal and protection (safeguarding resources, if a company has them)
Supporting vulnerable populations adequately (offering rides and shelter)	More amenable regulatory environment (building positive partnerships for good working relationship for future negotiations)
Information gathering and data access (gaining disaster-related data)	Stronger connections with local communities (providing support in disaster situations)
Direct communication to a subset of population (alerting drivers and customers)	

3.6.3) Sharing Economy Limitations

While these benefits might indicate that leveraging the sharing economy could be a major strategy in evacuating residents, experts were clear that there are numerous drawbacks to using shared resources. These limitations are important to highlight, particularly as this strategy is new and largely untested. Experts offered challenges that can be grouped into three areas: 1) personnel, 2) congestion and communication, and 3) equity (Table 6). Beyond these categories, other limitations could pose problems. These include:

- Conflicts between expansion-oriented model of most sharing economy companies and the humanitarian model of governments in disasters;
- Low supply of drivers/hosts in many U.S. cities in contrast to the evacuation needs of a community;
- Lack of trust in strangers or companies; and
- Language barriers in providing service.

Several experts were strongly opposed to the sharing economy as a general evacuation strategy (as shown in Figure 1 above) and noted a number of the limitations in Table 6. These strongly opposed experts were mostly concerned about pre-disaster planning and communication infrastructure required to properly distribute shared resources in a disaster. This was discussed in the context of a lack of sufficient resources (i.e., time, money) to develop partnerships. They also expressed distrust for private companies to act benevolently during the disaster. At the same time, several experts were concerned with congestion issues that could arise from the influx of shared resources, particularly vehicles into a disaster area. The inability of agencies to control these vehicles could significantly hamper the evacuation process for others. This concern over control was discussed in the context of a rapid terrorist attack in a downtown area. Experts were also worried about relying heavily on private resources to provide assistance, as agencies would not have control of drivers.

Most critically, questions remain in the structure and mechanics of any future partnerships in evacuations. Memoranda of Understanding are a first step to establishing the groundwork for cooperation. Future partnerships could include legally-binding agreements, as well as guidelines and procedures for surge flagging. The total number of expert mentions of these various policy mechanisms are provided in Figure 1 above.

Table 6: Key Sharing Economy Limitations by Experts (n=24)

Personnel	Congestion and Communication	Equity
Ensuring drivers/hosts show up and arrive on time in risky conditions	Increasing number of vehicles attempting to evacuate	Determining who shoulders service costs
Paying and increasing the number of drivers without surge pricing	Changing destinations due to the sparser distribution of Airbnb houses	Overcoming the digital divide (i.e., inequality in accessing computers/Internet)
Ensuring safety of providers and users of shared services	Changing traffic patterns due to reliance on GPS systems	Ensuring low costs for those most vulnerable
Reaching sufficient driver/host knowledge of how to handle unique situations, such as correctly assisting an older individual or an individual with limited mobility to a vehicle	Failing to match drivers and riders due to communication issues (i.e., power outage)	
Determining liability (i.e., who is responsible for safety and guaranteeing rides or housing)	Overloading the wireless network	

3.7) Hurricane Irma Survey Results and Discussion

To supplement the expert interview findings and begin to assess sharing economy feasibility in evacuations, we offer empirical results from the Hurricane Irma survey. Survey respondents resided primarily in three Florida counties: Brevard, Lee, and Collier. Hurricane Irma heavily impacted Lee and Collier counties and a large portion of Brevard evacuated. Other counties that we targeted included: Miami-Dade (3.7%), Broward (2.9%), Monroe (2.6%), and Pinellas (2.5%). Respondents were predominately white (94.0%), well educated (only 6.5% with a high school degree or less), mostly female (81.9%), drivers (94.3% drive to work alone), and higher-income (30.1% above $100,000 for household). This skew is a function of the areas surveyed along the predominately wealthier coastlines of Florida and the use of an online survey that requires Internet access. Overall, age, employment status, household size, housing type, length of residence, and hazard experience were more evenly distributed. Moreover, 97.4% of respondents were the sole, primary, or equal household decision-maker. Regarding mandatory evacuation orders, 69.5% reported that they were ordered to evacuate and did so, 30.5% reported that they were ordered to but did not evacuate, 46.4% reported that they were not ordered but still evacuated, and 53.6% reported that they were not ordered and did not evacuate. This is comparable to results from a telephone poll of registered voters that found the split for those given mandatory orders to be 57% evacuated and 43% not evacuated (Mason-Dixon Polling and Research, 2017). Our survey indicates a higher amount of mandatory evacuation compliance that may be a result of the targeted focus on Lee, Collier, and Monroe counties where Irma made landfall (i.e., non-representativeness of the sample). Another possible explanation for the difference is that evacuees often have misconceptions over evacuation terminology, in particularly what notices are mandatory versus voluntary (Lindell et al., 2019). With different jurisdictions using variable language for evacuation orders, some individuals may have thought they received a mandatory order when they only received a voluntary order. This is often an artifact of peer communication rather than official sources (Lindell et al., 2019). Additional demographic information on the survey respondents can be found in Table A1 of the appendix.

One key area of interest was how willing individuals would be to offer accommodations or transportation to other evacuees in a future disaster. Respondents were given four scenarios to consider which are described in Table 7 below. We also asked respondents a series of questions regarding their current use of the sharing economy and use during Hurricane Irma (Table 8). Table 8 below also includes the results of the sharing scenarios.

Table 7: Description of Sharing Scenarios for Future Disaster

Scenario	**1**	**2**	**3**	**4**
Resource Type	Sheltering	Sheltering	Transportation	Transportation
Label	S1-Shelter-Cost	S2-Shelter-Free	S3-Transport-Before	S4-Transport-During
Number of Respondents	645 (all)	645 (all)	368 (evacuees only)	368 (evacuees only)
Explanation of Scenario	Individual's willingness to offer to shelter other evacuees at a **cost per night**	Individual's willingness to offer to shelter other evacuees **for free**	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
Additional Information to Survey Taker	Shared home is safe and has not been ordered to evacuate		No additional information	
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)			

Table 8: Sharing Economy Use and Likelihood to Share in a Future Disaster

Current Usage of Sharing Economy (n = 645)

Frequency	**TNC**	**Carsharing**	**Homesharing**
Regularly (several times a week or more)	0.9%	0.0%	0.2%
Often (about once a week)	1.4%	0.0%	0.2%

Sometimes (several times a month)	11.9%	0.5%	2.0%
Rarely	33.0%	2.8%	33.3%
Never	51.0%	86.4%	62.2%
I don't know what this	1.7%	10.4%	2.2%

Use of Sharing Economy in Hurricane Irma Evacuation (n = 368)

Decision	TNC	Carsharing	Homesharing
Yes (for both evacuation and reentry)	0.8%	0.0%	
Yes (for evacuation only)	0.0%	0.0%	
Yes (for reentry only)	0.3%	0.0%	5.4%
No	98.9%	100.0%	94.6%

Likelihood to Use or Share Shelter Resources in a Future Disaster (n = 645)

Likelihood	Use Airbnb as Shelter in Evacuation	S1-Shelter-Cost	S2-Shelter-Free
Extremely likely	18.3%	6.7%	19.2%
Somewhat likely	27.8%	17.5%	20.3%
Neither likely nor unlikely	13.6%	12.4%	13.3%
Somewhat unlikely	16.1%	26.2%	13.3%
Extremely unlikely	24.2%	37.2%	33.8%

Likelihood to Share Transportation in a Future Disaster (n = 368)

Likelihood	S3-Transport-Before	S4-Transport-During
No personal vehicle	2.7%	2.7%
Extremely likely	29.1%	23.6%
Somewhat likely	25.3%	24.2%
Neither likely nor unlikely	10.1%	10.1%
Somewhat unlikely	16.8%	18.5%
Extremely unlikely	16.0%	20.9%

Most respondents are not frequent TNC, carsharing, or homesharing users. About 11.9% of respondents sometimes use TNCs, and approximately 33% rarely use TNCs and homesharing. Carsharing usage was extremely low, and over 10% of respondents did not know what it was. These low values parallel use during Hurricane Irma. Only 1.1% used TNCs for some aspect of the evacuation, and no one used carsharing. This was expected given the prevalence of auto ownership in many areas of Florida, particularly those most impacted by Hurricane Irma. However, 5.4% used homesharing, and almost 18% of respondents said they would be extremely likely to use Airbnb as a shelter for a future hurricane. These results suggest a rise in homesharing interest for evacuation accommodations. Over 17% said that they knew about the Airbnb Disaster Response Program (Open Homes).

Table 8 indicates that very few respondents (6.7%) were extremely likely to offer shelter to an evacuee at a cost (S1-Shelter-Cost). However, we found that a larger proportion (19.2%) were willing to provide shelter to an evacuee for free (S2-Shelter-Free), indicating some respondent compassion. Respondents were somewhat willing to share at 17.5% and 20.3% for S1-Shelter-Cost and S2-Shelter-Free respectively, which represents individuals who might be persuaded to help. However, a large proportion was extremely unlikely to share, which indicates a "ceiling" in willingness to share. For S3-Transport-Before and S4-Transport-During, individuals were more willing to help provide transportation than sheltering. This may reflect the higher inconvenience of sheltering an evacuee for extended periods of time as compared to transporting an evacuee in a day or over several hours. Over 29% of respondents were extremely willing to share for S3-Transport-Before, and 23.6% were extremely willing to share for S4-Transport-During. We also find that a sizable number were extremely unlikely to share transportation, but it is less pronounced than sheltering. Additional descriptive statistics were used to help determine the current capacity of transportation and sheltering resources available and individuals' reservations in sharing resources (Table 9).

Table 9: Current Capacity and Reservations for Sharing Sheltering and Transportation

Number of Spare Beds/Mattresses (n=645)	
0	16.0%
1	25.1%
2	28.4%
3	16.9%
4	7.8%
5	2.6%
More than 5	3.3%
Charge Per Night to Rent to Evacuee (n=645)	
$0	56.0%
$1-$40	17.1%
$41-$80	9.3%
$81-$120	4.4%
$121-$160	0.5%
$161-$200	0.2%
More than $200	2.9%
No answer	9.8%
Reservations About Renting to Evacuee (n=645)	
Uncertainty about one's own safety or security	74.1%
Feeling responsible for the additional house guest(s)	60.9%
Having to interact with a stranger	51.6%
Not having enough water and/or food	45.7%
Disruption of everyday tasks	36.6%
General dislike of hosting	33.2%
Not having enough space for the additional guest(s)' belongings	31.6%

Having to drive the individuals around	17.2%
No government oversight	7.8%
Other	16.1%
I do not have reservations	1.2%

Number of Spare Seatbelts Across All Evacuating Vehicles (n=368)

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%

Maximum Time Deviation to Provide Transportation (n=368)

No time deviation	10.1%
Less than 10 minutes	4.1%
10-19 minutes	18.8%
20-29 minutes	17.9%
30-39 minutes	19.8%
40-49 minutes	3.5%
50-60 minutes	8.2%
Over 60 minutes	4.1%
No answer	13.6%

Maximum Miles Carrying to Provide Transportation (n=368)

No distance	7.1%
Under 10 miles	3.8%
10-19 miles	11.1%
20-29 miles	13.6%
30-39 miles	6.0%
40-49 miles	4.3%
50-99 miles	11.9%
100-199 miles	9.8%
Over 200 miles	15.5%
No answer	16.8%

Reservations of Providing Transportation (n=368)

Uncertainty about one's own safety or security	57.9%
Not having enough space for the additional passenger(s)' belongings	54.3%
Feeling responsible for the additional passenger(s)	47.3%
Not having enough fuel	40.8%
Having to interact with a stranger	40.8%
Adding extra time to the evacuation	39.7%
Having to deviate from evacuation route	30.2%
Having to drive the individual(s) for a long period of time	25.0%
Not having enough water and/or food	22.0%

No government oversight	4.3%
Other	12.5%
I do not have any reservations	2.4%

As shown in Table 9, we find that most individuals have spare beds and mattresses to house evacuees, and only 16.0% have no spare bed/mattress. In addition, respondents were moderately unwilling to charge people for sheltering, perhaps indicating some disaster-context compassion. This phenomenon, more typically known as altruistic behavior or the therapeutic community, has been extensively studied in disasters (see Tierney et al., 2001 and Lindell et al., 2006 for summaries). From a sample of just evacuees, we found that 77% of evacuating vehicles had at least two spare seatbelts, while just 11.1% had no seatbelts. We note that two spare seatbelts would be sufficient for one evacuee and their luggage. This indicates that evacuating vehicles were not fully used during the Hurricane Irma evacuation. Interestingly, 37.2% of respondents were open to carrying an evacuee over 50 miles, which is not insignificant. However, 50.9% were only willing to deviate a maximum of 30 minutes from their evacuation route, and 10.1% were unwilling to deviate at all. These results suggest that a potential passenger's proximity to the evacuation route is a key factor.

We also asked respondents about their reservations with sharing transportation or sheltering (Table 9 above). Similar to willingness to share findings, respondents tended to have more reservations related to sheltering than transportation. Safety/security was the top reservation for both resources, with 74.1% stating concerns for sheltering and 57.9% for transportation. The value for sheltering is likely due to the personal nature of hosting an evacuee at one's home. Feeling responsible for the individual(s) was also a major concern (60.9% and 47.3%), along with having to interact with a stranger (51.6% and 40.8%). Approximately 54% were also concerned about having enough space for the passenger(s) belongings in the case of transportation.

In summary, we found that spare capacity exists for transportation and sheltering in disasters. Moreover, some individuals were extremely willing to share, albeit with significant reservations. These results indicate that resident-oriented networks of shared resources could be feasible in an evacuation. Indeed, research has found that TNCs could be a viable evacuation strategy in China, despite some limitations (Li et al., 2018). On the demand side, Li et al. (2018) found that 83% of carless individuals would opt to take shared mobility in a hypothetical disaster, indicating a clear community need for shared resources.

3.8) Limitations Discussion

3.8.1) Study Limitations

While this research makes notable contributions to understanding shared resource evacuation strategies, it has several limitations. First, the interviews may not capture the breadth of expert opinions, despite the steps taken to gather a diversity of experts. Second, experts opted into the study, indicating some self-selection bias. This is especially notable for sharing economy companies of which only two were willing to participate. Attempting to overcome this limitation, we targeted our search to high-ranking agency officials in large cities with a strong presence of sharing economy companies. The online survey also reflects some self-selection bias, as individuals opt into the study. We attempted to address this by providing a lottery incentive and by seeking assistance from over 20 agencies with different jurisdictions to help distribute the survey. We acknowledge online surveys have some sampling bias. Online surveys only reach individuals with Internet access, oversampling younger individuals (Kaplowitz et al., 2004) and oversampling wealthier populations (Sheehan and Hoy, 1999). We also found that for our survey, the sample geographies were wealthier, more highly educated, and racially whiter than Florida. However, our survey did reach a wide range of ages, household types, lengths of residence, and evacuation experience. Our online survey method allowed us to access a unique population of evacuees, reduce the time needed to conduct the survey, lower the monetary costs associated with survey research, and increase the complexity of the survey (Wright, 2005). The online sampling also reduced sample bias related to displaced individuals who may have a new physical address.

With these sampling limitations in mind, we note several impacts on our results. Two key demographic characteristics exhibited bias in the sample: income (skews to higher-income) and vehicle ownership (skews to more vehicles). We hypothesize that these two variables would bias our results upward for spare capacity. We found that spare capacity in seatbelts and beds is relatively even across income group, indicating little to no impact on results. However, when we calculate the number of spare seatbelts by vehicle ownership, we find that there is an increase in spare seatbelts as vehicle ownership increases. Most critically, since we severely undersampled carless individuals, we note that any result on spare seatbelts is significantly over-estimated. Additional details on these calculations and analyses can be found in Table A2 and Table A3 in the appendix.

Moreover, some respondents may have been confused about the term “spare seatbelts.” We do not know if respondents accounted for space that would be taken by luggage. This deficiency in the survey design likely biases the results on capacity upwards. In future surveys, this question should be composed of two parts: 1) the number of total seats with seatbelts available across evacuating vehicles and 2) the number of seats with seatbelts occupied by people, luggage, and pets across evacuating vehicles. The difference of these two numbers would be the spare capacity. We also mention that a spare seatbelt only refers to *potential* capacity. Indeed, most evacuees carry luggage, which occupy some seats. The *actual* capacity is likely to be lower in an evacuation. Consequently, a ratio of two seatbelts per user of shared resources is a more realistic assumption for policy development.

We also note that peers (e.g., family and friends) are often used for sheltering accommodations. In our survey, we found that 15.8% of evacuees sheltered with friends, and 43.5% of evacuee sheltered with family. This reflects similar results presented in the literature review (e.g., Lindell et al., 2019). The preference for accommodations via peers biases our spare capacity calculations for beds upwards. While this limitation diminishes the number of spare beds available for other evacuees, this does not diminish the goal of shared resources—leveraging unused capacity. Indeed, friends and family may be vulnerable during disasters and may require transportation and sheltering. Networks of friends could be a pathway for increasing shared resources.

Another limitation is that our sample biases significantly toward females (81.9%), which may impact willingness to share. However, we find that this oversampling has little impact on the likelihood to share, as women and men stated they would be extremely likely to share at similar rates. We also hypothesize that income could impact willingness to share, with those with a higher-income more likely to share their assets since they have more resources. However, we find that likelihood to share across the four scenarios is relatively consistent across income groups. While there are small differences, they are not enough to make any concrete conclusion regarding the potential bias. Additional details focused on willingness to share and these two demographic variables can be found in Table A4 and Table A5 in the appendix.

We also note that a number of other demographic characteristics that were slightly under- or over-sampled could impact our results (e.g., age, education, household size, homeownership). To overcome these sampling limitations, we recommend that further research should incorporate multi-variate modeling tools, such as discrete choice analysis, to determine the factors that impact willingness to share. This is a clear next step for research on shared resources in evacuations.

3.8.2) Additional Considerations for the Sharing Economy

We also provide additional considerations for the sharing economy in disasters. We note the availability of sharing economy resources will be highly dependent on geography and hazard type. Some geographies may not require a significant amount of private resources – from companies or other residents – even in a disaster. Moreover, the level of coordination within jurisdictions between government and private companies or residents will differ drastically. For example, some jurisdictions may prohibit vehicles to enter evacuation zones or travel near hazards, diminishing their usefulness in providing transportation. This restriction may also be different depending on the hazard. For example, for hazards with substantial lead time (e.g., hurricanes), all TNC rides would need to be conducted prior to any evacuation zone restrictions. Shared resources will not be a *primary strategy* for evacuating or sheltering residents, but a tool in the response toolkit. Most evacuations continue to be dominated by personal automobiles and sheltering in peer residences. Nevertheless, providing transportation and sheltering to some evacuees – including peers – could be crucial to saving lives and improving evacuation outcomes. The sharing economy has the potential to better allocate resources, even among peers.

We also note that the sharing economy is highly dependent on communication and technology. However, disaster situations may lead to power and communication outages that hamper technological strategies. The sharing economy could contribute to a network overload, as individuals attempt to match over the Internet. We recognize that this is a key limitation, especially for catastrophic disasters. However, for smaller, localized disasters where utilities continue functioning, sharing could be a feasible tool for evacuation logistics. Moreover, the ability to share resources would not be impacted in areas outside the anticipated impact region. To combat catastrophic event limitations, significant planning may be necessary. For a community-based approach, individuals will have to identify carless neighbors ahead of time, and community organizations would have to match members and evacuees in advance. At public shelters, transportation sharing may require physical carpooling boards for trips to stores and health appointments. Sheltering would also require planning in advance through neighbors or community organizations. A similar approach would be needed for private companies to plan in advance where to send drivers and contact potential hosts. We note that advanced planning for evacuation logistics is not only applicable for the sharing economy but also other forms of transportation and sheltering that may be impacted by power and communication outages.

Finally, we recognize that the sharing economy could be an equitable strategy for transporting and sheltering individuals. However, as asserted by the experts, different vulnerable groups could also face considerable challenges accessing and using the sharing economy. For example, some may be unable to request rides or shelters if they do not have technology access (digital divide). Overcoming this divide may require low-tech solutions, including options to call for rides and shelters, rather than solely offering a smartphone app. For example, call-in strategies have been used before in disasters to coordinate shared transportation through faith-based organizations, non-governmental organizations such as social services, and emergency management agencies (Lindell and Perry, 1992). Another strategy may be to leverage 2-1-1, a public service hotline that provides information about resources via landlines. Research has found that 2-1-1 was a critical tool in disasters (Bame et al., 2012) and has assisted vulnerable populations (Hall et al., 2012). Moreover, 2-1-1 call patterns could be used to more adequately deploy disaster resources for unmet needs (Bame et al., 2012). Strategies may also require person-to-person contact or physical bulletin boards.

Individuals with disabilities may also face difficulties requesting services due to a lack of accessible vehicles or communication mechanisms. Other groups, such as immigrants, may have difficulty navigating English-only applications or services. Moreover, individuals may be hesitant to accept services from strangers, especially if providers do not have proper emergency or situational training. These challenges limit the potential of the sharing economy. Consequently, we recommend that additional equity research to identify vulnerable groups, along with identifying the benefits and challenges for each group to better assess feasibility. We recommend that this be achieved through an equity framework (such as STEPS, which stands for Spatial-Temporal-Economic-Physiological-Social as seen in Shaheen et al., 2017), along with in-depth interviews or focus groups with vulnerable populations.

3.9) Recommendations

To consolidate the results and discussion, we developed a set of actionable policy recommendations for public officials at emergency management and transportation agencies at all levels of government. We formed these recommendations (Table 10) based on the expert interviews and the survey results. Given the current low usage of the sharing economy in evacuations based on the survey results, these policy recommendations are a first step in constructing a practice-ready framework for agencies to increase the amount of assets at their disposal. Policies are ordered by general feasibility and recommendation level. We also divided the policy recommendations into two categories: company- and resident-oriented. While there remain numerous challenges to shared resources, the recommendations act as a launching point to encourage agencies to consider adding shared resources – whether from companies or residents – into strategies for evacuation and sheltering response.

Table 10: Policy Recommendations for Shared Resources in Disasters

Company-Oriented			**Resident-Oriented**		
Policy Concept	**Description**	**Recommendation**	**Policy Concept**	**Description**	**Recommendation**
Creating partnerships with sharing economy companies	Companies have an extensive network of assets that can be leveraged quickly. However, asset availability depends on the willingness of drivers/hosts to participate. Partnerships also require substantial planning, and some people may not trust companies to help in disasters.	Recommended for larger cities with a strong presence with sharing economy companies	Bolstering neighborhood /community networks	Private residents may be a more trustworthy source of resources and assets (i.e., neighbors) and have capacity and willingness to share. However, the decentralized nature of sharing resources may lead some to forgo helping, especially if the disaster is dangerous for the provider. Activating resources will also take more time.	Recommended for all communities, but especially smaller localities without the presence of sharing economy companies
Policy Lever, Mechanism, or Strategy for Shared Resources in Disasters					
Stakeholder Communication	Requires agencies to set up a working relationship with companies and include them in stakeholder meetings	Highly recommended for all jurisdictions	Community-Based Outreach	Increases the amount of information available about how to help other people in disasters and specifically target reservations individuals may have	Highly recommended for all jurisdictions
Alliance Development	Encourages companies to connect with a non-governmental organization (NGO) that builds an alliance of private companies for emergency purposes	Highly recommended for all jurisdictions with an NGO focused on private companies	Integration into CERT	Includes shared resource strategies and discussion in Community Emergency Response Team (CERT) training and encourages leaders to implement strategies during a disaster	Highly recommended for jurisdictions with strong CERT teams
Training Exercises	Allows companies to observe or participate in training exercises	Highly recommended for jurisdictions with consistent exercises	Community Organization Outreach	Increases the amount of information available about how to help other people in disasters, but it is specifically geared to how local CBOs (e.g., social work non-profits, religious organizations, neighborhood associations) can leverage their networks	Highly recommended for all jurisdictions

Surge Flagging	Increases agency oversight of price gouging violations and requires a public information campaign	Highly recommended for all jurisdictions	Community Organization Control	Transfers some transportation and sheltering management and/or responsibilities to CBOs away from local governments or NGOs (e.g., American Red Cross, Salvation Army), if those entities become overwhelmed with transportation and sheltering demand	Moderately recommended and only if community organizations are well integrated, have wide networks, and are disaster ready
Pilot Programs	Tests the feasibility of partnerships through first- and last-mile connections, paratransit supplements, and/or driver retention mechanisms	Highly recommended for jurisdictions with a strong transportation company presence	Shared Resource Reserve Team	Creates a disaster-specific team (similar to CERT) that would spearhead resource sharing in disasters and would be required to assist	Moderately recommended since it would require extensive training and strong community cohesion
Memoranda of Understanding (MOU)	Creates informal partnerships between agencies and companies, beginning first with information sharing and situational awareness	Moderately recommended for all jurisdictions, as companies may not have capacity for multiple MOUs	Matching Program	Develops a program to specifically match providers and shared resource recipients	Not recommended as this system would be time-consuming to construct and may require a smartphone app
Formal Contracts	Creates formal partnerships between agencies and companies, which sets parameters for information sharing and asset sharing under set conditions	Moderately recommended and only after successful MOUs			
Reimbursement Schemes	Allows companies and drivers to receive funds in return for providing a service	Not recommended as companies already offer services for free (or steeply discounted) to users in disasters			

3.10) Conclusions

This paper contends that the sharing economy could be a source of moderate to substantial benefits to help solve current problems faced in emergency management. Nevertheless, it is just one tool in the evacuation strategy toolkit. We first found through archival research that sharing economy companies have acted in 30 U.S. disasters and their involvement in disasters has been steadily growing. Next, expert interviews (n=24) revealed that the sharing economy has a number of benefits and limitations in evacuations. Benefits include increasing the number of resources available, assisting vulnerable groups, moving assets more quickly especially in no-notice events, sharing information, and situational awareness. Limitations include ensuring that drivers/hosts are available, determining who pays for the resources, overcoming the digital divide, and reducing the impact of vehicles on congestion.

Based on the Hurricane Irma survey, we found minimal sharing economy use in this evacuation. However, we found that spare capacity in the form of spare seatbelts and beds/mattresses exists (just 11.1% had no spare seatbelts and 16.0% had no beds/mattress). Respondents were fairly willing to deviate from their evacuation routes at least 20 minutes (53.4%) and carry evacuees at least 20 miles (61.5%). Moreover, we discovered a relatively high *stated* willingness of disaster-impacted individuals to provide these resources, especially for transportation before the evacuation (29.1%), transportation during the evacuation (23.6%), and sheltering for free after the evacuation (19.2%). We note that there is a clear "ceiling" in this willingness: at least 20% of the sample would be extremely unlikely to share transportation, and 30% would be extremely unlikely to share housing. This indicates that regardless of the situation, these individuals would not share resources. Moreover, respondents had a number of concerns about the sharing economy, especially safety. Social equity is another major consideration.

While there are a number of limitations that must be overcome, this paper argues that the sharing economy could constitute an additional and innovative tool for evacuations that could solve some issues including: resource deficiency, slow responsiveness, poor communication, and low support for vulnerable groups. Moving forward, emergency management and transportation agencies could consider developing policies that leverage sharing economy company assets; address potential concerns (e.g., digital divide, equity, and safety); and maximize benefits to emergency preparedness, response, and recovery.

3.11) Acknowledgements

This research was made possible through the openness and flexibility of the interviewed experts in sharing their time and knowledge. We would also like to acknowledge numerous emergency and transportation agencies, cities, and planning councils across Florida who distributed the survey. The opportunity to explore this topic was made possible by the Graduate Research Fellowship Program, which is administered by the National Science Foundation. The Transportation Sustainability Research Center at UC Berkeley also provided generous support to this research. We also acknowledge that aspects of this paper were presented at the Transportation Research Board Annual Meeting in 2018. Finally, we would like to thank the two anonymous reviewers who provided thoughtful comments for improving this paper.

3.12) Appendix

Figure A1: Actions of Sharing Economy Companies During Disasters in the U.S.

Year	Event	Actions
2012	**Hurricane Sandy** New York City, NY	Approximately 375,000 people were ordered to evacuate from low-lying areas. Multiple counties in New Jersey also received evacuations (Preston et al. 2012). Uber placed a 2x surge price on all rides, revoked the surge after public pressure, and reinstituted it by giving all proceeds to the driver (Casabian 2012; Walk 2012). Nearly 400 people on Airbnb provided their space for free for evacuees (Airbnb 2017a).
2013	**Winter Storm Nemo** Boston, MA	Uber placed a 2x surge price on all rides and promised to donate all profits from surging to the American Red Cross (Haydu 2013).
	Winter Storm Electra New York City, NY	People reported Uber surge pricing as high as 8x and publicity was highly negative (Shontell 2013).
2015	**Winter Storm Juno** Boston	Uber surge pricing was capped at 2.9x and all additional proceeds were donated to the Red Cross. Lyft kept pricing at 2x the normal rate (Boroyan 2015). Lyft suspends service during the travel ban (Lyft 2015).
	Winter Storm Juno New York City, NY	Uber surge pricing was capped at 2.8x and 20% of the fare plus $1 per ride was donated to the Red Cross. Lyft kept pricing at 2x the normal rate (Walsh 2015). Lyft suspended service during the travel ban (Boroyan 2015).
	Winter Storm Linus Boston, MA	Uber provided information that 80% of fare from Linus and Juno went to Uber drivers. In addition, over $100,000 was donated to the Red Cross (Uber Boston 2015).
	Houston Floods Houston, TX	Uber provided an option for Houston residents to pick an UberRELIEF car with the same fare as an UberX, but $1 per ride is donated to the American Red Cross (Uber Houston 2015). Airbnb waived all fees for renters in the area who provide a room for free (Meyerland Community Improvement Association 2015).
	Austin Floods Austin, TX	Both Uber and Lyft produced statements acknowledging the flooding, attempting to keep their drivers away from flooded areas (Moore 2015). Uber offered two trips to and from the Flood Assistance Center in Austin with $20 off each ride. A specific promotion code had to be entered to receive the discounted rides (Adams 2015).
	Texas Tornados Dallas-Ft. Worth, TX	Uber provided an option for Dallas-Fort Worth residents to pick a Red Cross car, which had the same fare as an UberX, but $1 per ride was donated to the American Red Cross (Uber Dallas 2015).
	Missouri and Illinois Floods St. Louis, MO	Uber provided an option for St. Louis residents to pick an UberRELIEF car, which had the same fare as an UberX, but $1 per ride was donated to the American Red Cross (Uber St. Louis 2015).
2016	**Louisiana Floods** Baton Rouge, LA	Over 20,000 were evacuated across Southern Louisiana. Some people remained behind, leading to over 1,000 rescues (PBS 2016). Uber New Orleans offered discounted rides to people in the flood zones. People in Lafayette received a $20 credit to or from the flooding emergency center, while people in Baton Rouge received a $15 credit to or from three different emergency centers. Uber also committed $10,000 to the American Red Cross (Uber Louisiana 2015). Airbnb distributed a letter to its users in the South Louisiana and waived all fees for renters who provided space for free (Goff 2016).

Hurricane Matthew
Southeast U.S.

- Over 2 million people across 4 states were ordered to evacuate. Officials were especially tough, stating that assistance would not be provided to those who stayed (Jacobo et al. 2016).
- Uber and Lyft capped their surge pricing to 2x the base fare (Byrd 2016).
- Airbnb activated numerous regions including central North Carolina, Atlanta, Orlando and Tampa Florida, and central South Carolina. All fees were waived (Wanshel 2016).

2017

Oroville Dam Crisis
Oroville, CA

- Just under 200,000 were evacuated in case of a dam failure (Schmidt et al. 2017).
- Airbnb activated housing in the Oroville-Chico-Sacramento area. All fees were waived (Airbnb 2017b).

Hurricane Harvey
Southeastern Texas, Louisiana

- Despite mandatory evacuations in multiple counties in Southeast Texas and Louisiana, no evacuation orders were given for Houston, causing a contenious battle between the Mayor of Houston and the Governor of Texas (Rosenblatt 2017). The decision to not evacuate was questioned by multiple media outlets.
- Uber pledged $300,000 in rides, food, and relief while Lyft pledged $100,000 for a relief fund. Uber offered free rides up to $50 to and from over 60 evacuation shelters. Lyft halted its operations to protect its drivers, waived the commission fee for drivers when operations restarted, and set up its Round Up & Donate program for donations to the American Red Cross (Uber Austin 2017; Lyft 2017a).
- Airbnb activated housing in the Houston Area for over two weeks and over 700 hosts offered housing. All fees were waived (Airbnb 2017c).

Hurricane Irma
Florida, Georgia, South Carolina

- In the largest evacuation in U.S. history, mandatory and voluntary evacuation orders were given to almost 7 million people across Florida, Georgia, and South Carolina (Anderson and Galofaro 2017).
- Uber pledged $400,000 in rides, food, and relief. Uber provided up to 5 free rides up to $25 to and from shelters in multiple counties and cities in Florida. In some cities, Uber also offered free rides to and from hospitals. Uber suspended service, coordinated with local partners to deliver supplies and give rides to volunteers, gave free meals to law enforcement, worked with local partners to give rides to vulnerable older adults, and donated to long-term relief programs (Uber Athens 2017; Uber Florida 2017). Lyft donated $100,000 to Relief Rides, which helped individuals get to and from hospitals and shelters, and partnered with Team Rubicon to assist in transporting miltiary veteran volunteers. Lyft conierge service allowed individuals to request rides without smart-phones and the Round Up and Donate program was in effect. Lyft supended service during the storm (Lyft 2017b).
- Airbnb activated housing across Florida, Georgia, and South Carolina for over one month. All fees were waived (Airbnb 2017d).

Las Vegas Shootings
Las Vegas, NV

- Uber refunded all rides in Las Vegas around the time and place of the shootings, offered rides to and from hospitals and reunification centers of up to $50 and gave free rides to and from United Blood Services donation centers. Profits received by drivers were unchanged by these actions. Lyft immediately suspended Prime Time, donated free rides to and from hospitals, reunification centers, and blood centers for up to $40 for two rides (Korosec 2017).
- Airbnb activated housing in the Las Vegas region for over two weeks and over 100 hosts offered housing. All fees were waived (Airbnb 2017e).

Northern California Wildfires
North San Francisco Bay Area

In a rapid and chaotic evacuation, thousands evacuated, some without orders, as the wildfires spread quickly. For all fires, almost 100,000 people evacuted (Nelson and Kohli 2017)

Uber committed $300,000 worth of rides, food, and relief and partnered with the American Red Cross to help with rides to and from shelters (Cheng 2017). Uber also offered free rides to Project Open Hand clients (up to 4 rides of $10 each) to and from filtered air centers at libraries around San Francisco (Project Open Hand 2017). Lyft offered 5 rides up to $15 each to and from evacuation centers and partnered with McKesson to provide rides to and from hospitals and treatment centers in the impacted areas (Lyft 2017c; McKesson 2017).

Airbnb activated housing in the San Francisco Bay Area for over three weeks and over 900 hosts offered housing (Airbnb 2017f).

Southern California Wildfires
Greater Los Angeles Area

Evacution orders were given for multiple fires in the Greater Los Angeles Area including the Thomas Fire, the Creek Fire, the Rye Fire, and the Skirball Fire to over 200,000 total people (Kipling and Harris 2017).

Uber offered free rides up to $50 to and from evacuation centers in the Los Angeles Area and helped provide free meals to first responders through Uber Eats (Uber Los Angeles 2017; ABC News 2017). Lyft offered evacuees free rides up to $40 to and from evacuations and continued their partnership with United Way through the Round Up and Donate Program (Lyft 2017d).

Individuals were encouraged to sign up for the new Airbnb Open Homes program to provide housing to evacuees (Blumberg 2017).

2018

Montecito Mudslides
Ventura and Santa Barbara Counties, CA

Evacution orders were issued across Ventura County and Santa Barbara county to over 20,000 (Kennedy 2018).

Uber offered rides up to $30 to several evacuation centers and hospitals in the Santa Barbara county area (Yamamura 2018).

Kilauea Volanco Eruption
Hawai'i, HI

Uber capped surge pricing on Hawai'i and offered free rides to evacuees (Sims 2018).

Airbnb activated its Open Homes program across the island of Hawai'i (Airbnb 2018b).

Mendocino Complex Wildfire
Mendocino and Lake Counties, CA

Evacution orders were issued across Lake County and Mendocino County to over 15,000 people (CBS SF 2018a).

Airbnb activated housing for individuals impacted by wildfires across Northern California, including the Mendocino Complex Fire (Ukiah Daily Journal 2018).

Carr Wildfire
Redding, CA

Evacution orders were issued in the Redding area to 38,000 people (Neuman 2018).

Lyft offered rides to seniors and volunteers through its Lyft Relief Rides program using partnerships with the American Red Cross and United Way (CBS Sacramento 2018).

Airbnb activated housing for individuals impacted by wildfires across Northern California, including the Carr Fire (Ukiah Daily Journal 2018).

Hurricane Florence
North Carolina, South Carolina, Virginia

Evacution orders were issued to over one million across three states (Fausset 2018).

Uber committed $300,000 worth of rides, food, and relief and partnered with the American Red Cross to help with rides to and from shelters. Rides could be redeemed up to $25 to and from evacuation centers (Rivas 2018). Lyft activated is Relief Rides program, partnered with United Way and the Office of the Virginia Governor to provide free transportation in the evacuation, and offered $30 ride credits following the storm. Lyft also partnered with the American Red Cross to help provide rides to volunteers (Lyft 2018a).

Airbnb activated its Open Homes Program and over 600 hosts offered their homes on the platform (Airbnb 2018c).

Hurricane Michael
Florida, Georgia

Over 375,000 people were issued mandatory evacuation orders (Lazo and Berman 2018).

Uber offered rides up to $25 to and from evacuation centers, coordinated with local partners to provide transportation to volunteers and first respondents, and provided discount meals to law enforcement (Uber 2018). Prior to the storm, Lyft provided rides through United Ways' 2-1-1 program. For recovery, Lyft offered $15 ride credits in Panama City, Florida for travel and parterned with the American Red Cross and Team Rubicon to deploy volunteers (Lyft 2018b).

Airbnb activated its Open Homes Program and over 1000 hosts offered their homes on the platform (Airbnb 2018d).

Central Texas Floods
Central Texas (18 counties)

Airbnb activated its Open Homes Program and over 150 hosts offered their homes on the platform for the floods (Airbnb 2018e).

Camp Fire
Butte County, CA

Over 50,000 people were ordered to evacuate, specifically 27,000 from Paradise, CA (CBS SF 2018b) in one of the deadliest wildfires in U.S. history.

Lyft partnered with United Way and offered two free rides up to $15 in the Chico area (Stampler 2018).

Airbnb activated its Open Homes Program and over 2000 hosts offered their homes on the platform (Airbnb 2018f).

Woolsey Fire
Ventura and Los Angeles Counties, CA

Over 200,000 people were issued mandatory evacuation orders (Cosgrove et al. 2018).

Uber offered two rides up to $50 to and from evacuation centers (Stampler 2018). Lyft partnered with United Way and offered two free rides up to $15 in Southern California (Stampler 2018).

Airbnb activated its Open Homes Program and over 1600 hosts offered their homes on the platform for the Woolsey Fire and nearby Hill Fire (Airbnb 2018g).

2019

Tennessee Floods
Tennessee

Airbnb activated its Open Homes Program and over 150 hosts offered their homes on the platform for severe weather and flooding that impacted Tennessee (Airbnb 2019a).

Lee County Tornados
Lee County, AL

Airbnb activated its Open Homes Program and over 150 hosts offered their homes on the platform for the Lee County tornados in Alabama. The region for hosts extended into Georgia (Airbnb 2019b).

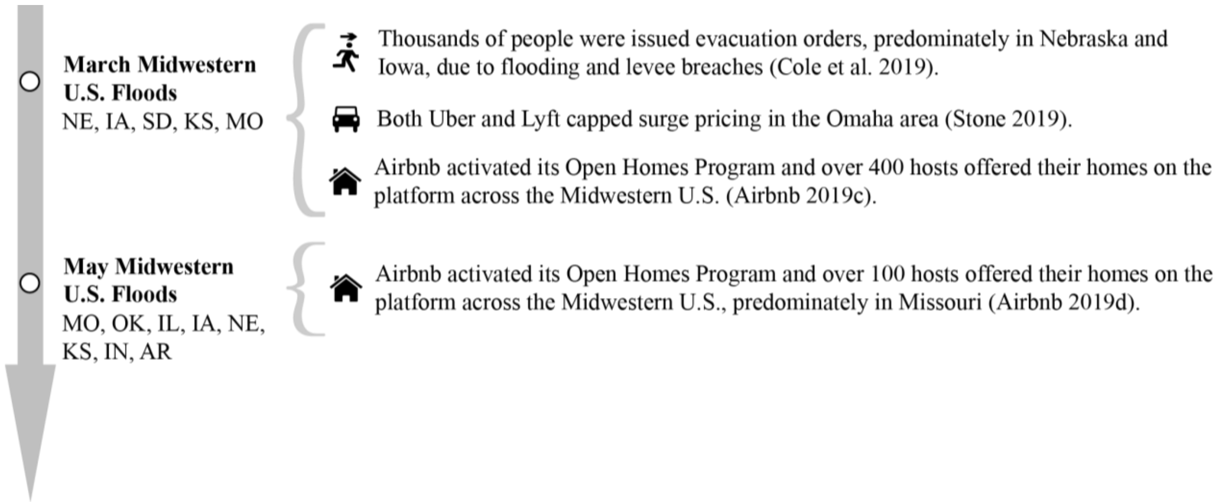


Table A1: Demographic Characteristics of Hurricane Irma Survey Respondents (n=645)

Evacuation Choice	
Received Mandatory Order, Evacuated	69.5%
Received Mandatory Order, Stayed	30.5%
No Mandatory Order, Evacuated	46.4%
No Mandatory Order, Stayed	53.6%
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%
Live in FEMA* Flood Risk Area	
Yes	39.5%
No	47.9%
I don't know	12.6%
* Federal Emergency Management Agency	
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%
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%
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%
Pacific Islander	0.2%
Native American/Alaska Native	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%
2-year degree	12.9%
4-year degree	32.1%
Professional degree	26.4%
Doctorate	3.6%
Employment	

$100,000 - $149,999	17.7%
More than $150,000	12.4%
No/prefer no answer	11.8%

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%

Household Characteristics

Household with Disabled	16.4%
Household with Children	44.8%
Household with Elderly	15.0%
Households with Pets	77.1%

Access to Internet at Home

Yes	98.3%
No	1.7%

Mobile Phone Type

Own a smartphone	96.3%
Own a non-smartphone	3.4%
Do not own a cell phone	0.3%

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%

Primary Transportation Mode for Work/School

Drive alone using automobile	94.3%
Work from home	1.7%
Carpool/vanpool	0.9%
Bus	0.8%
Bicycle	0.6%
Motorcycle/scooter	0.3%
Walk	0.3%
Shared mobility	0.2%
Rail	0.0%
Other	0.9%

Previous Hurricanes Experienced

0	3.6%
1 or 2	31.3%
3 or 4	17.5%
5 or more	47.6%

Previous Evacuations Experienced

0	46.4%
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%

Table A2: Number of Spare Beds and Spare Seatbelts by Income

	0 Beds	*1 Bed*	*2 Beds*	*3 Beds*	*4+ Beds*	*N*
Under $20,000	16.7%	26.7%	33.3%	13.3%	10.0%	30
$20,000-$39,999	37.5%	26.3%	16.3%	13.8%	6.3%	80
$40,000-$59,999	20.2%	33.3%	26.3%	10.1%	10.1%	99
$60,000-$99,999	11.4%	22.9%	32.5%	18.7%	14.5%	166
$100,000 and More	11.3%	20.6%	32.0%	18.0%	18.0%	194
No answer	9.2%	28.9%	23.7%	23.7%	14.5%	76

Income	0 Seatbelts	1 Seatbelt	2 Seatbelts	3 Seatbelts	4+ Seatbelts	N
Under $20,000	15.4%	0.0%	7.7%	23.1%	53.8%	13
$20,000-$39,999	10.2%	6.1%	22.4%	18.4%	42.9%	49
$40,000-$59,999	12.5%	6.3%	9.4%	23.4%	48.4%	64
$60,000-$99,999	8.8%	6.9%	18.6%	14.7%	51.0%	102
$100,000 and More	8.2%	12.2%	11.2%	18.4%	50.0%	98
No answer	21.4%	11.9%	7.1%	9.5%	50.0%	42

Table A3: Number of Spare Seatbelts by Vehicle Ownership

Vehicle Ownership	0 Seatbelts	1 Seatbelt	2 Seatbelts	3 Seatbelts	4+ Seatbelts	N
1 Vehicle	12.1%	6.1%	12.1%	24.2%	45.5%	99
2 Vehicles	10.0%	10.5%	16.0%	16.0%	47.5%	200
3+ Vehicles	13.4%	6.0%	10.4%	11.9%	58.2%	67

Table A4: Likelihood to Share Resources by Gender

S1-Shelter-Cost

	Extremely Likely to Share	Not Extremely Likely to Share	N
Female	7.2%	92.8%	528
Male	4.3%	95.7%	117

S2-Shelter-Free

	Extremely Likely to Share	Not Extremely Likely to Share	N
Female	19.7%	80.3%	528
Male	17.1%	82.9%	117

S3-Transport-Before

	Extremely Likely to Share	Not Extremely Likely to Share	N
Female	27.2%	72.8%	302
Male	37.9%	62.1%	66

S4-Transport-During

	Extremely Likely to Share	Not Extremely Likely to Share	N
Female	23.2%	76.8%	302
Male	25.8%	74.2%	66

Table A5: Likelihood to Share Resources by Income Level

S1-Shelter-Cost (all respondents)

Income	*Extremely Likely to Share*	*Not Extremely Likely to Share*	*N*
Income			
Under $20,000	16.7%	83.3%	30
$20,000-$39,999	6.3%	93.8%	80
$40,000-$59,999	8.1%	91.9%	99
$60,000-$99,999	7.8%	92.2%	166
$100,000 and More	2.6%	97.4%	194
No answer	9.2%	90.8%	76

S2-Shelter-Free (all respondents)

Income	*Extremely Likely to Share*	*Not Extremely Likely to Share*	*N*
Under $20,000	23.3%	76.7%	30
$20,000-$39,999	21.3%	78.8%	80
$40,000-$59,999	19.2%	80.8%	99
$60,000-$99,999	22.9%	77.1%	166
$100,000 and More	16.0%	84.0%	194
No answer	15.8%	84.2%	76

S3-Transport-Before (evacuees only)

Income	*Extremely Likely to Share*	*Not Extremely Likely to Share*	*N*
Under $20,000	23.1%	76.9%	13
$20,000-$39,999	34.7%	65.3%	49
$40,000-$59,999	23.4%	76.6%	64
$60,000-$99,999	33.3%	66.7%	102
$100,000 and More	23.5%	76.5%	98
No answer	35.7%	64.3%	42

S4-Transport-During (evacuees only)

Income	*Extremely Likely to Share*	*Not Extremely Likely to Share*	*N*
Under $20,000	15.4%	84.6%	13
$20,000-$39,999	22.4%	77.6%	49
$40,000-$59,999	23.4%	76.6%	64
$60,000-$99,999	25.5%	74.5%	102
$100,000 and More	21.4%	78.6%	98
No answer	28.6%	71.4%	42

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Chapter 4: Trust and Compassion in Willingness to Share Mobility and Sheltering Resources in Evacuations: A Case Study of the 2017 and 2018 California Wildfires

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ABSTRACT
Advances in the sharing economy – such as transportation network companies (e.g., Lyft, Uber) and home sharing (e.g., Airbnb) – have coincided with the increasing need for evacuation resources. While peer-to-peer sharing under normal circumstances often suffers from trust barriers, disaster literature indicates that trust and compassion often increase following disasters, improving recovery efforts. We hypothesize that trust and compassion could trigger willingness to share transportation and sheltering resources during an evacuation.

To test this hypothesis, we distributed a survey to individuals impacted by the 2017 Southern California Wildfires (n=226) and the 2018 Carr Wildfire (n=284). We estimate binary logit choice models, finding that high trust in neighbors and strangers and high compassion levels significantly increase willingness to share across four sharing scenarios. Assuming a high trust/compassion population versus a low trust/compassion population results in a change of likelihood to share between 30% and 55%, depending on scenario. Variables related to departure timing and routing – which capture evacuation urgency – increase transportation sharing willingness. Volunteers in past disasters and members of community organizations are usually more likely to share, while families and previous evacuees are typically less likely. Significance of other demographic variables is highly dependent on the scenario. Spare seatbelts and bed capacity, while increasing willingness, are largely insignificant. These results suggest that future sharing economy strategies should cultivate trust and compassion before disasters via preparedness within neighborhoods, community-based organizations, and volunteer networks, during disasters through communication from officials, and after disasters using resilience-oriented and community-building information campaigns.

Keywords: Evacuations, sharing economy, shared mobility, ridehailing, homesharing, California wildfire

4.1) Introduction

Beginning with Hurricane Sandy in 2012, the sharing economy has been active in 30 disasters in the United States (U.S.) through home sharing (e.g., Airbnb) and transportation network companies (TNCs, also known as ridesourcing and ridehailing) (e.g., Lyft, Uber) (Wong et al., 2018a; Chapter 3). While early sharing economy company actions were largely ad hoc, recent actions stem from highly structured disaster relief policies. For example, during the Woolsey Wildfire (2018) in Southern California, Lyft and Uber both offered ride credits to and from evacuation centers, while Airbnb activated its Open Homes Program, allowing hosts to offer free housing to evacuees (Chapter 3). Even with these private company resources, public agencies may still lack resources to evacuate and shelter all citizens, particularly for mass hurricane evacuations and mass wildfire evacuations (e.g., Carr Wildfire, Camp Wildfire, and Woolsey Wildfire in California in 2018). A significant number of people also continue to have poor access to transportation, sheltering, or both. Consequently, shared resources from private citizens could encourage more individuals to evacuate and improve equitable outcomes.

Despite considerable literature in evacuation logistics and behavior (Lindell et al., 2019), the feasibility of the sharing economy in evacuations as a potential logistical strategy remains largely unstudied (Wong et al., 2018a; Wong and Shaheen, 2019), along with influencers of this sharing behavior. Under normal circumstances, individuals have significant reservations about sharing resources, especially with respect to trust. This becomes more problematic with persistent myths of looting and social discontent during disasters (Tierney et al., 2006). Concurrently, compassion through resource support, charitable donations, and recovery assistance is widespread across disasters. In 2017 and 2018, roughly 30% of U.S. households donated money to disaster aid, while 12% volunteered in a disaster (Indiana University Lilly Family School of Philanthropy, 2019).

Thus, we hypothesize that two social variables – trust and compassion – influence willingness to share in an evacuation. To test this hypothesis, we distributed two surveys to individuals impacted by the: 1) 2017 December Southern California Wildfires (n=226) and 2) 2018 Carr Wildfire (n=284). We first present background on evacuation logistics, the sharing economy, trust, and compassion in disasters. Next, we describe our methodological approach of employing binary logit choice models across four hypothetical sharing scenarios to identify influencers of willingness to share. We then present logistic, trust, compassion, and sharing concern results from our survey and discuss the models for both wildfires. Finally, we conclude with several recommendations for building a sharing economy evacuation strategy.

4.2) Literature

In this section, we discuss several related areas from the literature including: 1) evacuation logistics, 2) the sharing economy in disasters, 3) social capital, trust, and compassion in disasters, and 4) literature gaps.

4.2.1) Evacuation Logistics

Evacuations require multiple logistic resources – specifically transportation and shelter – to ensure that individuals are safe. Lindell et al. (2019) reviewed this literature, describing that evacuation logistics involved evacuee's transportation mode, number of vehicles, route, destination, and shelter. Most work on evacuation logistics has largely assessed the modal split or shelter type split, which indicate the demand level. Resource demand, in turn, impacts evacuation metrics (e.g., evacuation time estimates), which can be managed through mechanisms that typically increase supply (i.e., reversing lanes via contraflow).

For transportation, hurricane evacuation studies have found that many evacuees use a personal vehicle, ranging from 87% to 96% of evacuees (Prater et al., 2000; Lindell et al., 2011; Wu et al., 2012; Wilmot and Guidshala, 2013; Wu et al., 2013; Wong et al., 2018b). These same studies found that between 2% and 10% received a ride from someone else, while 1% or less used public transit. Evacuees also often took extra vehicles, ranging from 1.10 vehicles to 2.15 vehicles per household (Prater et al., 2000; Lindell et al., 2011; Wu et al., 2012; Wu et al., 2013). Households sometimes take additional vehicles to transport all household members, pack additional luggage, or protect the vehicle(s) from the disaster.

Sheltering is another key evacuation logistic that indicates housing demand, including public shelters. Across hurricane studies, the majority of evacuees stayed with friends or family, ranging from 44% to 70% (Prater et al., 2000; Whitehead, 2003; Smith and McCarty, 2009; Cheng and Wilmot, 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 relatively low public shelter use (2% to 11%), while a significant number of evacuees used hotels/motels, ranging from 7% to 46%. Wong et al. (2018b) also found that 5% of evacuees used a peer-to-peer platform, such as Airbnb, to find sheltering for Hurricane Irma.

4.2.2) The Sharing Economy in Disasters

The sharing economy is a collection of Internet-based transactions where goods are shared or obtained (Hamari et al., 2016). For this study, we focus on several mobility sectors along with home sharing to potentially aid in disaster relief:

- Transportation Network Companies (TNCs): On-demand access where users request rides through a smartphone application.
- Carpooling: Grouping of travelers for trips that would have otherwise occurred.
- Carsharing: Short-term access to vehicles, while forgoing auto ownership costs.
- Bikesharing: On-demand access to bicycles for one-way or roundtrip travel.
- Scooter sharing: On-demand access to electric scooters for one-way or roundtrip travel.
- Home sharing: A marketplace for homes and rooms where people host and rent their space.

Three private companies – Airbnb, Lyft, and Uber – have been primary actors in disasters. Chapter 3 reviewed the sharing economy in evacuations by assessing past private company actions, interviewing experts in the emergency space, and surveying evacuees from Hurricane Irma. The research found some benefits of the sharing economy for public agencies (e.g., resource redundancy, supporting vulnerable populations, and information sharing opportunities) and private companies (e.g., positive press coverage, improved business continuity, and stronger community connections). Still, limitations included fostering driver and host reliability, ensuring safety, reducing surge pricing, determining liability, reducing congestion on roadways and wireless networks, and overcoming the digital divide (i.e., inequality in accessing computers/Internet).

Despite these limitations, private companies remain active in disasters. Airbnb deploys its Open Homes Program following most major disasters, allowing users to provide their home for free to evacuees (Airbnb, 2018). Lyft employs its Wheels for all Program, partners with organizations including the American Red Cross, United Way, and Team Rubicon, and offers ride credits to and from evacuation centers (Lyft, 2018). Uber operates its Global Security Center and offers ride credits to and from evacuation centers (Hawkins, 2018). Given the increased structure of disaster relief, private companies are likely to continue and improve their assistance.

Along with the business-to-peer mechanisms, the sharing economy also comprises private citizens who exchange goods and services via the Internet (peer-to-peer). For Hurricane Irma, Chapter 3 found that private citizens were moderately likely to share resources to evacuees for a future evacuation, but more so for transportation. Wong and Shaheen (2019) found similar results, while also conducting four focus groups of vulnerable populations (low-income, older adult, individuals with disabilities, and Spanish-speaking). All groups expressed low trust of both drivers and companies in disasters. Groups offered recommendations for developing a sharing economy framework, including planning in advance, widely disseminating resource opportunities, and building a community-based approach (e.g., neighbors helping neighbors). Other recent work has assessed shared mobility potential in China by surveying potential evacuees, experts, and TNC drivers (Li et al., 2018). While this study sampled respondents without disaster experience, it found shared mobility could be a viable evacuation option, including no-notice situations in city centers (Li et al., 2018). For carless individuals, 83% would have taken shared mobility in a hypothetical disaster. This research also found that shared mobility could reduce the number of intermediate trips (i.e., trips to pick up family members), thus decreasing total simulated evacuation trip time. Most recently, research conducted by Borowski and Stathopoulos (2020) assessed TNC potential for no-notice evacuations through a mode choice model that incorporated demographic variables, context, warning message content, and emotionality. Borowski and Stathopoulos (2020) found that perceived urgency from the given scenarios increased TNC use. Moreover, they found that young adults, those in unfamiliar locations, and people who needed to travel far distances were less likely to use established modes (i.e., personal vehicles, carpool, public transit). Finally, Chapter 5 found that some vulnerable groups could benefit from sharing economy resources in disasters, but severe limitations and barriers remain for many, particularly challenges related to finding vulnerable populations and training drivers and hosts to adequately assist individuals in need of special assistance. This study, along with Chapter 3, mark a key shift in recognition of shared mobility as possible transportation modes in disasters.

Other related work to the sharing economy strategy has focused on the role of social networks in evacuation decision making, finding that the strength of social networks is a key influencer of evacuation choices (Madireddy et al., 2015; Sadri et al., 2017a; Sadri et al., 2017b; Sadri et al., 2018). For example, Sadri et al. (2017a) found that social partners that contact each other daily and live near each other were more likely to both evacuate. The geographical proximity indicated that some special evacuation resources could be distributed and would help impact social partners' decision making in a similar manner.

4.2.3) Social Capital, Trust, and Compassion in Disasters

Despite the sharing economy development, the ad hoc method of sharing resources is not new to disasters. Volunteerism and an outpouring of humanitarian support have been regular aspects of disasters and serve as reminders of the ability of people to come together in a crisis for the greater good. Much of this support can be explained by the availability of social capital. In the social sciences, social capital has been thoroughly developed (see Bourdieu, 1985; Coleman, 1988; Burt, 1997; Portes, 1998; Woolcock, 1998; Putnam 2001; Szreter and Woolcock (2004) for examples). These early studies had different definitions of social capital, but consistently noted the role of social networks and trust and the function of social capital to achieve some positive end. For the purposes of this paper, we first use a traditional understanding of social capital from Szreter and Woolcock (2004) that subdivides the term into three distinct forms:

> <u>Bonding social capital:</u> "trusting and co-operative relations between members of a network who see themselves as being similar" (e.g., among family or friends);
>
> <u>Bridging social capital:</u> "relations of respect and mutuality between people who know that they are not alike in some socio-demographic (or social identity) sense (differing by age, ethnic group, class, etc.)" (e.g., between strangers); and
>
> <u>Linking social capital:</u> "norms of respect and networks of trusting relationships between people who are interacting across explicit, formal or institutionalized power or authority gradients in society" (e.g., between communities and governments).

Considering the context of social capital in disasters, we find it fitting to include a definition of social capital from Nakagawa and Shaw (2004), defining it as "the function of mutual trust, social networks of both individuals and groups, and social norms such as obligation and willingness toward mutually beneficial collective action."

A number of studies have further developed the concept of social capital by applying it to disasters (see Ritchie and Gill, 2007; Aldrich and Meyer, 2015 for overviews). Indeed, Meyer (2018) found 195 publications between 1998 and 2015 focusing on social capital and disasters, noting distinct differences in conceptualizing social capital as a private resource versus a collective resource. Meyer (2018) also found that the majority of work has studied social capital generally across disasters, with significantly fewer papers on wildfires. Regardless of the unit of analysis or disaster type, studies have focused on the influence of social capital for specific states of the disaster cycle, with a focus on preparedness, response, and recovery. Before disasters, social capital has been found to assist communities in preparing for natural disaster (Paton 2007). Paton (2007) found that preparedness intentions were heavily influenced by social capital in the form of trust in civic agencies that provided preparedness strategies (i.e., strong linking ties). In a study of both preparedness and recovery, Murphy (2007) determined that communities and their associated social capital (in the form of network ties) impacted disaster preparedness and recovery. The research also pointed to the need to determine the sufficiency of ties in social capital and that community involvement needed to occur in addition to official involvement, drawing on pre-existing organizations to develop resiliency (Murphy 2007). In a case of earthquake preparation, research found that having an individual in one's social network discuss preparations was a key factor in increasing preparedness (Heller et al. 2005). For wildfires, Bihari and Ryan (2012) employed statistical measures, finding that communities with higher community cohesion (i.e., social capital) were more likely to undertake preparedness such as clearing vegetation, engaging with proactive planning measures, and advocating for more community-based preparedness. It should also be noted that social capital can differ significantly by geography. For example, Straub et al. (2020) found that while rural communities often band together to increase preparedness and build resilience, they often lack relational ties with urban areas (due in part to lack of trust and low expectations of reciprocity), which decreases preparedness.

During disasters, individuals often turn inward to close relationships, which indicates strong bonding ties (Pelling and High 2005). However, this process has been found to be detrimental to bridging ties, decreasing general societal trust and interactions. Pelling and High (2005) also reviewed additional literature on social capital in disasters through the lens of climate change, noting that the formation, operation, and utility of social capital helped develop an understanding of individual response in disasters, especially those with multiple risks. Social capital in the form of networks was also found to be a key factor in evacuations (Dynes 2006). For example, Dynes (2006) described how socially isolated individuals often take less preventative actions and that groups and networks can help influence individuals to leave. Most critically, social networks can be crucial in increasing the willingness to provide both short- and long-term housing to others. At the same time, the evacuation process can be severely debilitating to evacuees in terms of breaking social capital bonds, leading to disorientation over multiple years (Cox and Perry, 2011). It should also be noted that social capital has limits in an evacuation (Litt, 2008; Elliot et al., 2010), as even populations with strong network ties and high social capital are unable to assist each other if everyone is vulnerable. One more recent study determined that social ties were an important factor in evacuee choice making, specifically the decision to leave or stay between an individual and social partners (Sadri et al., 2017a). Indeed, if an individual and social partner communicated regularly or lived close to each other, they were more likely to evacuate. This verifies other studies that have found that social influence (e.g., from peers) through social ties can impact one's decision to evacuate or stay (Riad et al.,1999; Hasan and Ukkusuri, 2011; Lovreglio et al., 2016).

The majority of research on social capital has focused on recovery, with much of the literature pointing to the power of strong community ties and social capital in improving recoveries (see Aldrich, 2012 for a detailed explanation). Bolin and Stanford (1998) found that since needs were unmet after the 1994 Northridge Earthquake, multiple NGOs and CBOs stepped forward by leveraging their extensive social networks. These community-based approaches were especially useful for post-recovery housing for marginalized populations. Chamlee-Wright (2010), in a review of social capital in disasters, noted multiple disaster cases where socially embedded resources proved vital for recovering communities. Chamlee-Wright and Storr (2009a) found that the level of social capital in neighborhoods heavily influenced the recovery process and that the reconstruction of strong social networks (such as churches as noted in Rivera and Nickels, 2014), allowed some areas of New Orleans to rebuild following Hurricane Katrina. Moreover, a strong sense of place was a strong motivator for returning to the Lower Ninth Ward (Chamlee-Wright and Storr, 2009b). Chamlee-Wright and Storr (2011), in a study of St. Bernard Parish after Hurricane Katrina, used in-depth interviews to find that social capital in the form of collective narratives (such as self-reliance) facilitated resilience and shaped recovery strategies. In an analysis of Hurricane Katrina evacuees, Hawkins and Maurer (2010) found that bonding ties were most critical for immediate support while strong linking and bridging ties were more useful for long-term recovery. Shaw and Goda (2004) also found that high social capital improved recovery outcomes, specifically reconstruction speed and satisfaction, through a case study of the 1995 Kobe Earthquake. The study noted that areas with high social capital and strong connections among residences were able to conduct collective decision-making, while communities with loose connections and newer developments were less able. Nakagawa and Shaw (2004) also provided substantial review of the role of social capital in disaster recovery and found communities with social capital to be highly effective in rescue and relief across two case studies. Despite the largely positive influence of social capital in disasters, Elliot et al. (2010) found important limits to social capital, discovering that residents of the Lower Ninth Ward during Hurricane Katrina received less network assistance from community members before, during, and after the disaster when compared to the more affluent Lakeview neighborhood. Moreover, the research found that despite inequalities in receiving assistance from personal ties, formal assistance (via NGOs, CBOs, and others) was largely equal between the two neighborhoods, but not proportional to need (Elliot et al., 2010). Haney (2018) in a study of flooding in Calgary found that while those most affected by the flood tended to increase their level of civic engagement and form new network ties, their attachment to place did not increase.

The full capacity of transportation and sheltering resources remains untapped in disasters, perhaps due to a lack of social capital, specifically related to trust. Individuals tend to distrust strangers and only 35% of Americans agreed that "most people can be trusted" (World Values Survey, 2014). Lack of trust can also be a major barrier to consuming collaboratively under even normal conditions (Möhlmann, 2015; Hamari et al., 2016). In disasters, research has found mixed results. Before disasters, research on low-income Mexican Americans found that individuals with higher levels of civic trust of other people were more likely to report higher preparedness levels. After disasters, impacted communities typically displayed higher levels of trust across countries and disaster types (Toya and Skidmore, 2014). However, trust of institutions (e.g., the government) was often lower (Hommerich, 2012; Miller and Rivera, 2011) and social trust substituted for these institutions and even markets (Yamamura et al., 2015). Other work found that trust levels did not change following disasters, and reciprocity (i.e., giving back to others who helped) was lower in impacted areas (Fleming et al., 2014). Using two surveys before and after the Tohoku Earthquake, Nakayachi (2015) found that trust of risk-managing organizations (e.g., for nuclear and earthquake) decreased, but trust of organizations not directly related to the disaster (e.g., for new infectious diseases, airplane accidents) remained the same or even increased. More positively, if social trust was high in a community before a disaster, then trust-increasing effects were larger compared to low trust communities (Dussaillant and Guzman, 2014). Finally, research has found that community engagement principles helped elevate both preparedness for disasters and community trust (Paton, 2007). Given these mixed results, low trust may decrease willingness (and eventual action) to provide shared resources in disaster.

While low trust may reduce sharing, compassion may overcome social capital and trust barriers and increase sharing behavior. Research has found that the human capacity for empathy spurred sentiments of pity or compassion, which led individuals to pursue humanitarian response (Carbonnier, 2015). Often, traumatic experiences have led to positive compassion changes to help form deeper relationships (Tedeschi and Calhoun, 1996). Other research found that community-based compassion through organizations has alleviated local victim suffering in disasters (Shepherd and Williams, 2014). Individuals also preferred policies that reflect compassion, which may be somewhat impacted by self-interest (Viscusi and Zeckhauser, 2006), and tended to be less compassionate for individuals who made high-risk decisions (i.e., knowingly living in a flood plain). Research has also found that empathy was predictive of the willingness to help but not predictive of actual actions to help victims (Marjanovic et al., 2012).

4.2.5) Key Literature Gaps

Despite considerable research on evacuation logistics, social capital, trust, and compassion, two key gaps remain. First, research on wildfire logistics remains sparse. Fischer III et al., (1995) interviewed evacuees from the Ephrata Fire, finding that most evacuees stayed with friends or family during the evacuation. For a hypothetical wildfire, Mozumder et al. (2008) found similar sheltering rates as hurricane evacuations (57% with friends and family, 29% in a hotel/motel, and 2% in a public shelter). However, with very few studies, the demand for evacuation resources (including transportation resources) remains largely unknown for wildfires. Second, research on why people may or may not be willing to share resources for evacuations is lacking. Chapter 3 and Wong and Shaheen (2019) only provided descriptive statistics on the capacity and willingness to share. Neither of these studies nor Li et al. (2018) identified factors that impact willingness to share. Borowski and Stathopoulos (2020) focused on TNC mode choice using stated preference data from only non-evacuees, assessing the demand for shared resources but not the potential capacity. Chapter 5 only researched vulnerable populations who would receive resources. Moreover, based on the disaster literature, social capital – especially indicators such as trust and compassion – could be critical influencers on willingness to share. This paper seeks to fill these literature gaps.

4.3) Methodology

We developed an online survey to better understand the role of trust and compassion in disasters for the 2017 and 2018 California wildfires. In this section, we present the survey distribution method, scenario development, the discrete choice models, and study limitations.

4.3.1) Survey Distribution

We distributed two surveys to individuals impacted by the: 1) 2017 December Southern California Wildfires (n=226) from April to June 2018 and 2) 2018 Carr Wildfire (n=284) from February to April 2019. The 2017 December Southern California Wildfires (shortened to the 2017 Southern California Wildfires in this paper) were a destructive series of wildfires – primarily composed of the Thomas, Creek, Rye, and Skirball Fires – that led to mass evacuations. The Thomas Fire was one of the largest fires in California history, burning over 280,000 acres and destroying more than 1,000 structures (Cal Fire, 2018a). The Carr Wildfire in 2018 was a destructive fire in Redding, California that required thousands to evacuate, burned over 121,000 acres, and destroyed more than 1,500 buildings (Cal Fire, 2018b).

The survey was distributed online with the help of local partnering agencies and organizations. We first developed a list of potential partners including transportation, public transit, and emergency management agencies, news media, community-based organizations (CBOs) and non-governmental organizations (NGOs). Potential partners were contacted and asked to post the survey to online sources including Facebook, Twitter, listservs, alert subscription services, and websites. Participants were incentivized with the chance to win one of five $200 gift cards for the 2017 Southern California Wildfires and one of ten $250 gift cards for the Carr Wildfire. After removing unfinished surveys and cleaning based on key questions, we achieved a survey sample of 226 for the 2017 Southern California Wildfires and 284 for the 2018 Carr Wildfire.

Demographics of the samples (2017 Southern California Wildfires and 2018 Carr Wildfire) can be found in Table A1 and are explained in-depth in Wong and Shaheen (2019). For our surveys, respondents were predominately female (73.9% and 69.7%), highly educated (77.5% and 59.2% with a four-year degree or higher), and mostly white (81.5% and 90.8%). Both samples had low participation from individuals with a high school degree or less (0.9%, 5.6%), Hispanics (11.1% and 5.3%), and young adults under age 25 (2.7% and 2.8%). In general, age was highly varied including 19.0% and 22.9% who were 65 or older. This aligns with the employment statistics with 57.1% and 47.9% employed full time and 22.1% and 26.1% retired. A fairly large percentage of the households in the samples (14.2% and 18.7%) had an individual with a disability. Household income from the previous year was generally high (48.7% and 33.4% at $100,000 or more), although some respondents had incomes below $50,000 (12.3% and 22.5%). The majority of participants from both wildfires lived in a single-family home (73.9% and 91.2%), while a minority of respondents had children present in the household (25.2% and 35.2%). The samples exhibited high technology usage as most respondents in both samples owned a smartphone (92.0% and 93.0%) and had access to the Internet at home (98.7% and 97.2%). Nearly all or all survey respondents owned/leased at least one personal vehicle (99.1%, 100%), with many reporting that they owned/leased three or more vehicle (29.7% and 42.6%). Most individuals had previously experienced a wildfire prior to the most recent wildfire (93.4% and 89.1%) but many less had evacuated (35.3% and 31.0%). Most respondents from the 2017 Southern California Wildfires were largely split between three counties: Ventura (43.8%), Santa Barbara (41.6%), and Los Angeles (13.3%). Almost all respondents from the Carr Wildfire resided in Shasta County (94.0%).

4.3.2) Scenario Development

To better understand the potential for shared resources in evacuations and recovery efforts, we created four scenarios related to resource sharing in a future evacuation. The scenarios assess willingness to share resources and are the dependent variables in our discrete choice models to better understand the factors that impact this willingness:

- S1-Shelter-Cost: Sheltering – Individual's willingness to offer shelter to other evacuees at a cost per night
- S2-Shelter-Free: Sheltering – Individual's willingness to offer shelter to other evacuees for free
- S3-Transport-Before: Transportation – Individual's willingness to offer a ride to other evacuees before the evacuation process begins
- S4-Transport-During: Transportation – Individual's willingness to offer a ride to other evacuees during the evacuation, enroute to the destination.

These sharing scenarios follow the same pattern as Wong et al. (2018a) and were designed to address potential opportunities for sharing. The two sheltering scenarios were designed to test if potential profit for hosts impacted willingness to share. The two transportation scenarios differ by temporal impact, which is less relevant for sheltering. Our goal is to determine whether sharing transportation is more effective before or during an evacuation. We focused entirely on free transportation in contrast to profit-based transportation scenarios, which is a limitation of our design. All respondents answered questions regarding each of the sheltering scenarios, while only evacuees answered the transportation scenarios. The individual(s) receiving assistance was not specified beyond "individual(s)." The scenarios asked for willingness on a scale with five options:

1) extremely likely, 2) moderately likely, 3) neither likely nor unlikely, 4) moderately unlikely, and 5) extremely unlikely.

4.3.3) Discrete Choice Models

We developed eight binary logit models to assess willingness to share, following the methodology of Ben-Akiva and Lerman (1985). For the analysis, we divided the "choice" of willingness to share into a binary decision: 1) extremely likely to share and 2) all other answers. This was chosen to better isolate individuals who would realistically share in a future disaster (i.e., stated willingness of extremely likely), which is why we did not estimate an ordered logit model. In our paper, we wanted to develop a distinction between people who would be extremely likely to share and those who would be moderately willing to share. We also tested several models taking advantage of heterogeneous parameters through a mixed logit model. We found strong insignificance of almost all random parameters, which is likely due to a single observation per individual. We estimated the binary logit models using the Python package *Pylogit* (Brathwaite and Walker, 2018). The binary logit models are presented emphasizing each of the following variable types: 1) trust and compassion; 2) demographic variables; 3) evacuation circumstances, and 4) urgency indicators. Urgency indicators are characteristics of the evacuation (specifically departure time and route choice) that highlight the stressful and difficult choice context in a disaster. This includes characteristics of the hazard (e.g., fire threat) and choice alternatives (e.g., police presence). We selected variables following recommendations in Ben-Akiva and Lerman (1985), consisting of variables that are significant, behaviorally important, and/or a correct *a priori* coefficient sign. We note that in several instances we retained some non-significant variables since they were behaviorally important with the correct *a priori* coefficient sign. The decision to retain insignificant variables, while less efficient, decreases bias in our results. We also conducted a sample enumeration for each scenario by setting all responses for trust and compassion variables to be one or zero, thus mirroring a highly trustful sample and very distrustful sample. This is supplemented by probability weighted cross tabulations of sharing choice and reservations to find potential differences in sharing concerns.

4.4) Results and Discussion

4.4.1) Wildfire Logistics

We first provide the wildfire logistic results for both wildfires (see Table 1 below and Table A2 in the appendix). We find that most individuals evacuated from both samples with low non-compliance rates (i.e., receiving a mandatory evacuation order but not evacuating). Shadow evacuation rates (i.e., not receiving a mandatory evacuation order but still evacuating) were high, most likely a result of poor communication throughout both wildfires. Evacuation travel times were concentrated between 30 minutes and several hours (see Table A2), suggesting short-distance evacuations. This is confirmed by destination choice: approximately two-thirds of respondents from both wildfires remained within county.

Table 1: Demographic Characteristics of Survey Respondents

	2017 Southern California Wildfires	2018 Carr Wildfire
All Respondents	*n=226*	*n=284*

Evacuation Choice		
Evacuated	77.4%	89.4%
Did Not Evacuate	22.6%	10.6%
Received Mandatory Evacuation Order		
Yes	61.1%	66.2%
No	38.9%	33.8%
Non-Compliance Rate *(out of individuals who received a mandatory order)*	13.0% *(n=138)*	3.2% *(n=188)*
Shadow Evacuation Rate *(out of individuals who did not receive a mandatory order)*	62.5% *(n=88)*	75.0% *(n=96)*
Evacuees Only	*n=175*	*n=254*
Departure Timing by Hour		
12:00 AM – 5:59 AM	22.9%	9.1%
6:00 AM – 11:59 AM	19.4%	7.9%
12:00 PM – 5:59 PM	20.0%	19.7%
6:00 PM – 11:59 PM	14.9%	63.4%
Mode Choice		
One personal vehicle	45.1%	33.9%
Two personal vehicles	40.6%	45.3%
More than two personal vehicles	8.6%	16.5%
Other (e.g., Recreational vehicle, aircraft, rental car, carpool, carsharing, truck and trailer, walk)	5.7%	4.4%
Open Seats with Seatbelts in Evacuating Vehicles		
0	29.7%	24.8%
1	6.3%	6.7%
2	14.3%	9.8%
3 or 4	25.1%	21.3%
5 or more	24.6%	37.4%
Primary Route by Road Type		
Highways	62.3%	39.4%
Major Roads	15.4%	17.5%
Local or Rural Roads	5.1%	9.8%
No Majority Type	17.1%	36.6%
Shelter Type		
A friend’s residence	30.3%	39.8%
A family member’s residence	32.6%	29.9%
A hotel or motel	22.9%	13.4%
A public shelter	3.4%	2.4%
Other (e.g., second residence, portable vehicle, peer-to-peer service)	10.9%	14.5%
Within County Evacuation		
Yes	66.3%	66.1%
No	33.7%	33.9%
Returned Home		
Yes	92.6%	96.9%
No	7.4%	3.1%

Spare Beds/Mattresses		
Yes	83.7%	89.5%
No	16.3%	10.5%

Note: Percentages may not add to 100% due to rounding

For mode choice, we found most respondents used one vehicle (33.9% to 45.1%) or two vehicles (40.6% to 45.3%) to evacuate. The Carr Wildfire had a higher number of evacuating vehicles, perhaps due to auto dependency in the Redding area. With a significant number of multi-vehicle evacuations, 64.0% and 68.5% of respondents had at least two spare seatbelts for the 2017 Southern California Wildfires and Carr Wildfire, respectively. For shelter choice, most respondents stayed with family or friends, which mirrors hurricane literature (Lindell et al., 2019). Hotels and motels were also popular, but under 4% stayed at a public shelter. A significant number of respondents also sheltered at more than one destination (see Table A2), suggesting shifting fire danger or inadequate long-term sheltering. Finally, most respondents did not use GPS while evacuating (see Table A2), suggesting that evacuees relied on their own experience or directions from officials.

4.4.2) Trust, Compassion, and Volunteerism

Next, we provide descriptive statistics on respondents' trust, compassion and volunteerism (see Table 2 below), finding similar results between the wildfires. While individuals trusted most people, the level of trust differed by group. Family and friends ranked the highest, followed by coworkers. Average trust (from a Likert scale of 1 to 5) of neighbors (m = 3.61 and m = 3.80) ranked slightly higher than trust of community members and individuals from other cities. Higher trust of neighbors and closer connections suggests focusing on these social networks for sharing resources. One difference was that respondents from the Southern California Wildfires had a higher trust of strangers (m = 3.50) than respondents from the Carr Wildfire (m = 3.00), indicating potential differences in sharing levels with strangers. Most respondents for both wildfires also perceived an increase in trust in the community following the wildfires, indicating the trust-building nature of disasters. Indeed, individuals who received assistance from neighbors and had strong personal networks experienced faster disaster recovery (Sadri et al., 2018).

Table 2: Trust, Compassion, and Volunteerism

	2017 Southern California Wildfires	**2018 Carr Wildfire**
Sample Size	*226*	*284*
General Trust of Most People		
Yes, it is possible to trust most people	68.6%	63.7%
No, we can never be too cautious	29.2%	36.3%
No answer	2.2%	0.0%
Change in Trust of Others in Community Following Wildfires		
Increased substantially	23.9%	20.1%
Increased moderately	30.1%	41.2%
Remained the same	39.8%	32.4%
Decreased moderately	3.5%	4.2%

Decreased substantially	0.4%	2.1%
No answer	2.2%	0.0%
Past Disaster Volunteer		
Yes	36.7%	33.5%
No	61.9%	66.5%
No answer	1.3%	0.0%
Volunteer for Wildfires		
Yes	44.2%	46.8%
No	54.9%	53.2%
No answer	0.9%	0.0%
Mean Trust of Groups of People (Out of 5)		
Family	4.66	4.61
Friends	4.35	4.48
Coworkers	4.02	3.95
Neighbors	3.61	3.80
Other Neighborhoods in Community	3.29	3.56
Other Cities	3.10	3.21
Strangers	3.50	3.00
Bus Drivers	3.60	3.64
Lyft/Uber Drivers	3.41	3.27
Taxi Drivers	2.37	3.20
Police	3.77	3.95
Government	3.62	3.56
Mean Compassion (Out of 5)		
General Compassion (GC)	4.20	4.14
Stranger Compassion (SC)	3.97	4.04
Helping Compassion (HC)	3.60	3.80
Not-Selfish Compassion (NSC)	3.57	3.40
Tender Compassion (TC)	2.62	3.82

GC: When I hear about someone (a stranger) going through a difficult time, I feel a great deal of compassion for him or her.
SC: I tend to feel compassion for people, even though I do not know them.
HC: One of the activities that provides me with the most meaning to my life is helping others in the world when they need help.
NSC: I would rather engage in actions that help others, even though they are strangers, than engage in actions that would help me.
TC: I often have tender feelings toward people (strangers) when they seem to be in need.

Note: Percentages may not add to 100% due to rounding.

About one-third of wildfire respondents were a past disaster volunteer, indicating strong networks to provide support. Moreover, around 45% of respondents were volunteers for the wildfires, revealing significant outpouring from the community for others. For compassion, we found similar average levels between the wildfires, except for tender compassion (i.e., tender feelings for strangers in need). In addition, non-selfish compassion (i.e., engaging in activities to help strangers before self-serving activities) had a low average score, but this could still impact willingness to share.

4.4.3) Concerns About Sharing

We also asked respondents about reservations they had with sharing resources in an evacuation (see Table 3). These questions were asked in the context of the shared resource scenarios for both transportation and sheltering. We found that concerns were very similar between the two datasets. Uncertainty about one's own safety and security was the largest concern for sheltering, followed by feeling responsible for additional house guest(s), disruption to everyday tasks, and having to interact with a stranger. These results indicate that potential hosts place high value in safety and liability, perhaps requiring a formalized system of matching to overcome these concerns. However, individuals were not concerned that a sharing strategy would not have government oversight, suggesting that a strategy could be carried out by NGOs, CBOs, and/or private companies.

For transportation, safety and security was still a major concern, but respondents were also highly worried about not having enough vehicle space for the additional passenger(s) belongings and adding extra time to the evacuation. These concerns were more prominent for the 2017 Southern California wildfires, which may reflect some geographical and cultural differences. Reservations about vehicle space could significantly hamper a sharing strategy, especially since vehicle "guest" passengers would be unlikely to split their households into different vehicles. Further, concerns about adding extra time could require dedicated pickup locations to ensure that drivers do not have to deviate far from their planned evacuation route. Indeed, evacuation route deviation was expressed as a concern by around one-third of participants. Feeling responsible for passengers was also a key concern for transportation. We note that having to interact with a stranger was much less of a reservation for transportation, suggesting a shared mobility strategy among private citizens may be more feasible in evacuations than a shared housing strategy.

Table 3: Concerns about Sharing Sheltering and Transportation in an Evacuation and During Recovery

Reservations of the Sharing Economy ***(Top Four Reservations Highlighted)***	**2017 Southern California Wildfires**	**2018 Carr Wildfire**
Reservations About Sheltering an Evacuee (Full Sample)	*n = 226*	*n = 284*
Uncertainty about one's own safety or security	55.3%	57.4%
Feeling responsible for the additional house guest(s)	48.7%	45.1%
Disruption of everyday tasks	42.0%	37.3%
Having to interact with a stranger	40.7%	35.9%
Not enough space for the additional guest(s)' belongings	29.6%	29.6%
General dislike of hosting	21.2%	20.4%
Having to drive the individuals around	12.8%	16.5%
Not having enough water and/or food	24.8%	24.3%
No government oversight	5.3%	3.9%
I do not have concerns/reservations	4.0%	9.5%
Concerns About Transporting an Evacuee (Evacuees Only)	*n = 175*	*n = 254*
Uncertainty about one's own safety or security	44.6%	48.4%
Feeling responsible for the additional passenger(s)	44.6%	25.6%
Not enough space for the additional passenger(s)' belongings	53.7%	42.9%

Adding extra time to the evacuation	56.6%	45.7%
Having to deviate from the evacuation route	39.4%	31.9%
Having to interact with a stranger	25.7%	16.9%
Having to drive evacuee(s) for a long period of time	22.3%	13.0%
Not having enough fuel	18.3%	16.1%
Not having enough water and/or food	8.0%	6.3%
I do not have any concerns/reservations	6.9%	13.0%
No government oversight	6.3%	1.2%

4.4.4) Willingness to Share Resources

In this section, we present modeling results for the willingness to share resources, which are organized by wildfire and by sharing sector (i.e., shelter and transportation).

4.4.4.1) 2017 Southern California Wildfires – Shelter

We found for the 2017 Southern California Wildfires that individuals were more willing to share housing for free (24.3% extremely likely) than at a cost (11.5% extremely likely). See Table 4 below. From modeling, trust and compassion variables were positive and significant for both S1-Shelter-Cost and S2-Shelter-Free. Those who perceived increases in community trust were more likely to share shelter, suggesting that newly established trust can increase resources. Young adults and lower-income households were more likely to share for S1-Shelter-Cost, perhaps due to familiarity with priced home sharing and possible monetary benefits. However, females and smaller households were less likely to share. For S2-Shelter-Free, families were less likely to share, perhaps due to safety concerns. Long-term residents and smaller households were also less likely share. Smaller households may have less space for an evacuee (including fewer available bedrooms). It is not readily clear why long-term residents were less likely to share, but the result may be related to a lack of trust of newcomers into their neighborhood. Spare capacity was positive for both S1-Shelter-Cost and S2-Shelter-Free but not significant, highlighting the more powerful role of trust and compassion in willingness to share.

4.4.4.2) 2017 Southern California Wildfires – Transportation

Compared to sheltering, individuals were significantly more likely to share transportation overall but also more so while evacuating (58.9%) than before evacuating (36.6%). In Table 4, we found that trust of neighbors was positive and significant for both S3-Transport-Before and S4-Transport-During, suggesting that neighbor-based resource pooling may be most effective. High tender compassion was also positive and significant for both scenarios, indicating high concern for others' welfare. Individuals who were part of a community organization were somewhat more likely to share for S3-Transport-Before, while past volunteerism increased willingness for both scenarios. Those with older adults in their household were also more likely to share, perhaps due to their knowledge of the evacuation needs of vulnerable populations. Again, long-term residents were less likely to share. In this case, these individuals may have conducted more pre-evacuation trips to prepare their property and gather supplies. Previous evacuees and lower-income households were less likely to share during the evacuation, perhaps due to past poor evacuation experiences and resource constraints, respectively. Those living in Ventura County were much more likely to share transportation during. For evacuation circumstances, sheltering with a friend increased willingness for S3-Transport-During. Evacuation circumstances increased willingness for S4-Transport-During, including spare seatbelts and receiving a mandatory evacuation order. Mandatory orders could be potential mechanisms to increase sharing by notifying evacuees of transportation needs in their community. Urgency indicators were also important, specifically the higher pressure from officials to leave and the high presence of police along the route adding to increased willingness. As such, officials, police, and other first responders may present a strategy for communicating resource needs to private individuals and encouraging sharing. We note that police presence is classified under urgency since law enforcement typically provides mandatory evacuation orders and/or traffic orders that are based on the current hazard situation.

4.4.4.3) 2018 Carr Wildfire – Shelter

We found 14.1% and 29.6% were extremely likely to share for S1-Shelter-Cost and S2-Shelter-Free, respectively, for the Carr Wildfire. We found positive and significant variables for trust and compassion, with an emphasis on trust of strangers and non-selfish compassion (see Table 5 below). For S1-Shelter-Cost, previous volunteers and members of community groups were more likely to share, indicating a potential avenue for a shared resource network. High-income households ($100,000 and above) were less likely to share for a cost, likely due to their lower need for additional income. Households with spare beds and previous evacuees were more willing to share, but the variables were slightly insignificant. For S2-Shelter-Free, smaller households were more likely to share, which differs from the 2017 Southern California Wildfires models. Other demographic characteristics for both sheltering scenarios were not significant but exhibited correct signs.

4.4.4.4) 2018 Carr Wildfire – Transportation

Respondents were extremely willing to share for S3-Transport-Before (48.4%) and S4-Transport-During (72.0%). Trust of strangers was significant and positive for S3-Tranport-Before, while overall trust impacted S4-Transport-During (Table 5). High non-selfish compassion was positive and significant for both scenarios, and high overall compassion was significant for S4-Transport-During. Most demographic variables were weak influencers except for households with children, who were much less likely to share for both scenarios. Young adults were less likely to share during the evacuation, which may be related to less experience driving during an evacuation. Interestingly, being part of an organization (e.g., arts/cultural, education/school/PTA, professional/trade, religious, social service/charitable) was negative for S3-Transport-Before, albeit insignificant. This finding runs counter to our other models. Homeowners were less likely to share for S4-Transport-During, perhaps because they wanted to defend their home and evacuate later. Spare capacity (i.e., more than three spare seatbelts) was positive for both scenarios but only significant for S4-Transport-During. For S3-Transport-Before, individuals who did not have any pre-evacuation trips were more likely to share, since they had more time to assist. However, individuals who stayed with family were much less likely to share. Interestingly, those who received a mandatory evacuation order were less likely to share. This is likely because they had little time to consider helping others before evacuating themselves. We also found urgency variables – high visual fire levels, high smoke, low visibility, and high traffic – to be positive and almost all significant for S3-Transport-Before. Very high fire danger and police presence was positive for S4-Transport-During, while the high presence of first responders was negative. These urgency variables suggest that disaster risk may trigger sharing, increasing empathy and concern for other evacuees.

Table 4: Estimation Results for Sharing Scenarios for the 2017 Southern California Wildfires

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

	S1-Shelter-Cost			**S2-Shelter-Free**			**S3-Transport-Before**			**S4-Transport-During**		
Survey Results: Extremely Likely to Share	**11.5%**			**24.3%**			**36.6%**			**58.9%**		
Variables	**Coef.**	**p-value**		**Coef.**	**p-value**		**Coef.**	**p-value**		**Coef.**	**p-value**	
Constant Share	-3.91	<0.01	***	-1.45	0.05	*	-2.69	<0.01	***	-1.25	0.02	*
Trust and Compassion												
High Trust of Friends	1.58	0.01	**	------	------		------	------		------	------	
High Trust of Neighbors	------	------		0.89	0.04	*	0.95	0.04	*	1.25	0.02	*
Perception of Substantial Increase in Community Trust	1.58	<0.01	***	1.04	0.01	**	------	------		------	------	
High Non-Selfish Compassion	1.04	0.08	†	------	------		------	------		------	------	
High Helping Compassion	------	------		0.78	0.03	*	------	------		------	------	
High Tender Compassion	------	------		------	------		1.29	<0.01	***	0.66	0.13	
Demographics												
Young Adult (Under 35)	1.03	0.05	*	------	------		------	------		------	------	
Female	-0.80	0.11		------	------		------	------		------	------	
Part of Organization	------	------		0.42	0.36		0.47	0.29		------	------	
Volunteer in Past	------	------		------	------		0.51	0.17		0.92	0.02	*

Used Homesharing Before	1.15	0.22		------	------		------	------		------	------	
Previously Experienced a Wildfire	------	------		------	------		0.69	0.35		------	------	
Previous Evacuee	------	------		------	------		------	------		-0.62	0.10	†
1- and 2-Person Household	-0.68	0.16		-1.09	0.02	*	0.40	0.29		------	------	
Household Income Under $50,000	1.15	0.09	†	------	------		------	------		-0.69	0.21	
Children Present in Household	------	------		-1.58	0.01	**	------	------		------	------	
More than 10 Years in Residence	------	------		-0.89	0.02	*	-0.76	0.04	*	------	------	
Older Adult(s) Present in Household	------	------		------	------		0.76	0.06	†	------	------	
Resident of Ventura County	------	------		------	------		------	------		1.13	<0.01	***
Any Spare Beds	0.62	0.42		0.56	0.28		------	------		------	------	
Evacuation Circumstances												
Received Mandatory Evacuation Order	------	------		0.36	0.32		------	------		0.43	0.26	
Any Spare Seatbelts	------	------		------	------		------	------		0.66	0.09	†
Shelter Choice - Friends	------	------		------	------		0.54	0.16		------	------	
Urgency Variables												
Very High Official Pressure to Leave	------	------		------	------		0.50	0.23		------	------	

Very High Presence of Police	------	------		------	------		------	------		1.44	0.02	*
Extremely Likely to Share: *Enumeration – All High Trust & Compassion Dummy Values = 0*	2.5%			14.8%			26.8%			52.0%		
Extremely Likely to Share: *Enumeration – All High Trust & Compassion Dummy Values = 1*	53.8%			67.6%			73.6%			84.7%		
Observations	226			226			175			175		
R-Squared	0.60			0.29			0.17			0.18		
Adjusted R-Squared	0.53			0.23			0.08			0.10		

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

Table 5: Estimation Results for Sharing Scenarios for 2018 Carr Fire

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

	S1-Shelter-Cost			**S2-Shelter-Free**			**S3-Transport-Before**			**S4-Transport-During**		
Survey Results: Extremely Likely to Share	**14.1%**			**29.6%**			**48.4%**			**72.0%**		
Variables	**Coef.**	**p-value**		**Coef.**	**p-value**		**Coef.**	**p-value**		**Coef.**	**p-value**	
Constant Share	-5.36	<0.01	***	-2.04	0.01	**	-0.25	0.64		1.05	0.17	
<u>*Trust and Compassion*</u>												

Moderate and High Trust of Strangers	1.14	0.01	**	0.59	0.09	†	0.70	0.07	†	------	------	
High Trust of Neighbors	0.57	0.18		------	------		------	------		------	------	
High Trust Overall	------	------		------	------		------	------		0.72	0.03	*
High Non-Selfish Compassion	0.93	0.03	*	1.98	<0.01	***	1.36	<0.01	***	1.68	0.02	*
High Overall Compassion	------	------		------	------		------	------		0.60	0.09	†
Demographics												
Young Adult (Under 35)	------	------		------	------		------	------		-0.88	0.05	*
White	------	------		-0.48	0.30		------	------		------	------	
Volunteer in Past Disaster	0.76	0.05	*	0.26	0.38		------	------		------	------	
Part of an Organization	1.02	0.06	†	------	------		-0.40	0.22		------	------	
Previously Experienced a Wildfire	------	------		------	------		------	------		-0.59	0.30	
Previous Evacuee	-0.47	0.25		------	------		-0.46	0.14		------	------	
1 and 2 Person Household	------	------		0.99	0.02	*	------	------		------	------	
Children Present in Household	------	------		0.40	0.37		-0.79	0.02	*	-0.73	0.03	*
Residence - Single Family Home	0.81	0.32		------	------		------	------		------	------	
Homeowner	------	------		------	------		------	------		-0.82	0.07	†
Household Income $100,000 and Above	-0.83	0.05	*	0.27	0.39		0.44	0.18		------	------	
Any Spare Beds	1.68	0.12		0.29	0.59		------	------		------	------	

Evacuation Circumstances												
Received Mandatory Evacuation Order	------	------		------	------		-0.73	0.03	*	------	------	
More than 3 Spare Seatbelts	------	------		------	------		0.28	0.38		0.91	0.01	**
0 Trips Before Evacuating	------	------		------	------		0.67	0.05	*	------	------	
Items to Tow	------	------		------	------		0.53	0.17		------	------	
Shelter Choice - Family	------	------		------	------		-1.18	<0.01	***	------	------	
Shelter Choice - Friends	------	------		------	------		------	------		0.63	0.06	†
Urgency Variables												
Very High Visual Fire Level	------	------		------	------		0.38	0.20		------	------	
Very High Smoke Level	------	------		------	------		0.82	0.01	**	------	------	
Very Low Visibility	------	------		------	------		1.37	0.04	*	------	------	
Very High Traffic Levels	------	------		------	------		0.58	0.06	†	------	------	
Very High Fire Danger Level on Route	------	------		------	------		------	------		0.88	0.08	†
Very High Presence of First Responders	------	------		------	------		------	------		-1.39	0.02	*
Very High Presence of Police	------	------		------	------		------	------		1.24	0.06	†
Extremely Likely to Share: *Sample*	**8.3%**			**20.8%**			**41.9%**			**55.1%**		

Enumeration – All High Trust & Compassion Dummy Values = 0				
Extremely Likely to Share: *Sample Enumeration – All High Trust & Compassion Dummy Values = 1*	**48.5%**	**75.6%**	**79.1%**	**94.7%**
Observations	284	284	254	254
R-Squared	0.52	0.24	0.19	0.3
Adjusted R-Squared	0.47	0.19	0.1	0.22

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

4.4.5) Willingness to Share: Key Takeaways

In the discrete choice analysis, we found a nuanced story among sharing scenarios and between the two sets of wildfires in 2017 and 2018. We found trust and compassion variables greatly increased willingness to share, particularly trust of strangers, trust of neighbors, and non-selfish compassion. Demographic variable influence was scattered across scenarios and wildfires with several notable exceptions. Volunteers in past disasters and members of community organizations were usually more likely to share, except for members of organizations (e.g., arts/cultural, education/school/PTA, professional/trade, religious, social service/charitable) who were less likely to share transportation before evacuating for the Carr Wildfire. On the other hand, previous evacuees and families were less likely to share, except for families interested in sharing their housing at no cost to evacuees for the Carr Wildfire.

We found some weak indication that higher-income households were more likely to share, except for sharing shelter for a cost (vs. sharing for free). We determined that long-term residents were less likely to share for the Southern California Wildfires (but not the Carr Wildfire), which may be tied to cultural differences between the impacted areas. The modeling results also indicated that most demographic variables were only significant for one or two scenarios (e.g., young adults, female, white, used homesharing before, older adults present in the household, homeowner, single family home residence). While demographics will differ by geography, these variables help pinpoint potential provider groups for a more generalized sharing strategy. We also tested a number of other demographic variables across all four scenarios (e.g., education, employment status, TNC experience, etc.) but found little significance. These results point to the greater importance of individual levels of trust and compassion for resource sharing.

Several evacuation circumstances were significant for some of the transportation scenarios (i.e., receiving a mandatory evacuation orders, number of trips prior to evacuating, shelter/accommodation choice during the wildfires). Spare capacity was sometimes significant in increasing willingness to share (especially for spare seatbelts), but we found that the variable for spare beds was typically insignificant. Spare capacity may be a prerequisite for sharing, but social variables may activate sharing behavior. Finally, we found several urgency variables for departure timing and routing impacted some transportation scenarios. Evacuees may realize that other neighbors need significant help and would perish without receiving transportation, indicating that sharing behavior is triggered by the urgency of disasters. Urgency variable were particularly important for the Carr Wildfire, suggesting that hazard and cultural characteristics may influence the degree to which urgency impacts sharing willingness.

Across the scenarios, we found similar model fit, except for sharing shelter at a cost. This is likely due to the very strong negative constant value, but this could also result from overfitting a smaller sample. We also conducted a brief sample enumeration for likelihood to share by transforming all trust and compassion variables into zeros (i.e., no respondents have high trust or compassion) and ones (i.e., all respondents have high trust or compassion). We found a significant range between a low trust/compassion population and a high trust/compassion population (between 30% and 55% difference depending on scenario), suggesting that very low trust/compassion communities and very high trust/compassion communities will have significantly different likelihoods (and eventual action) to share. Finally, the modeling results indicate that the four sharing scenarios produce unique behaviors that are not necessarily consistent. While it may be easier to construct a general framework that applies to sharing across these scenarios, the results suggest that the characteristics of the scenarios play an important role in willingness to share.

4.4.6) Concerns for Sharers and Non-Sharers

To supplement our understanding of the discrete choice results, we also conducted a weighted sample aggregation by the different reservations for sheltering and transporting an evacuee. For this analysis, we used the prediction probabilities calculated for each model and the individual results for each concern/reservation. The result is a weighted percentage of sharers and non-sharers who stated they had reservations about sharing resources (Table A3 and A4). While this cross tabulation by sharing choice and concern/reservation could have been conducted without our models, we note that the choice probabilities now factor in the different independent variables that influence sharing choice. Consequently, these probabilities are a consistent estimate of the number of sharers and non-sharers for each concern/reservation (see Train, 2009 for more on aggregation).

We found that across the sheltering scenarios for both wildfires, more non-sharers had concerns/reservations regarding sharing housing than sharers. While this was expected, we found especially high divergence between sharers and non-sharers for uncertainty about safety and security, feeling responsible for the evacuee, and disruption of everyday tasks. Overall, the sharers for the S2-Shelter-Free scenario had more reservations than sharers for the S1-Shelter-Cost scenario. This result is likely due to the higher percentage of individuals who were willing to share in the S2-Shelter-Free scenario. This indicates that concerns/reservations do not remain constant or decrease even as willingness increases, suggesting that sharers are still highly worried about aspects of sharing in an evacuation. Between each of the wildfires, we found that sheltering sharers had similar concern/reservation levels. However, the Carr Wildfire non-sharers generally had fewer concerns/reservations for both sheltering scenarios than the Southern California Wildfire non-sharers. This difference mirrors the concern/reservation results presented in Table 4 and is likely due to cultural differences and/or wildfire context differences. We note that the separation between wildfires is not enough to make any concrete conclusions, suggesting fairly strong consistency in reservations.

For transportation, we found that more non-sharers had concerns/reservations than sharers for S3-Transport-Before for both wildfires. However, we found that sharers had more concerns/reservations than non-sharers for S4-Transportation-During. This result is impacted by two factors: 1) high predicted choice probabilities for sharers in the discrete choice models, which influences aggregated probabilities upward and 2) real and substantial concern from sharers about this scenario. Two of the strongest concerns/reservations where sharers and non-sharers diverge are associated with the scenario itself (having to deviate from the evacuation route and adding extra time to the evacuation). We note that these concerns/reservations may not be enough to convince someone not to share, but they indicate that these concerns will need to be addressed, if employing sharing economy resources in a disaster/recovery effort. Between the wildfires, Carr Wildfire non-sharers for both scenarios had less reservations than the Southern California non-sharers. This indicates that addressing these transportation reservations would likely yield a less meaningful behavioral change for the geography impacted by the Carr Wildfire.

4.5) Recommendations

From the wildfire logistic results, we developed several evacuation recommendations for local agencies (see Table 6). We also provide specific recommendations derived from the modeling results to help build a strategy for private resource sharing in evacuations. We also link the recommendation to previous work in the disaster field (albeit not necessarily wildfire research), particularly related to the role of CBOs and NGOs in disaster recovery and relief. We acknowledge in advance that many of these recommendations require additional research and pilot programs to determine exact communication and organizational mechanisms. We recommend that future research on the sharing economy strategy in evacuations focus on newly formed sharing programs, such as the Neighborhood Evacuation Team Program in San Diego County (Moe, 2020).

Table 6: Local Agency Recommendations

SoCal = 2017 December Southern California Wildfires		*Carr = 2018 Carr Wildfire*	
Recommendations from Descriptive Statistics and Modeling Results			
Recommend-ation	**Evidence**	**Discussion**	**Supporting Literature**
Increase community trust and compassion as part of disaster preparedness to increase willingness to share resources	Trust, especially trust of neighbors and strangers, significantly increased willingness to share for most sharing scenarios. Compassion, especially non-selfish compassion and	Trust and compassion were important factors in willingness to share, but it is not guaranteed that communities have adequate trust or compassion levels. Multiple approaches may be necessary to increase trust and compassion prior to the disaster. Strategies might include building community cohesion through civic pride (e.g., identity, slogans, flags, campaigns), easy-to-replicate	Community Emergency Response Teams (CERTs) (Flint and Stevenson, 2010; Carr and Jensen, 2015) Community cohesion and

	tender compassion, significantly increased willingness to share for most sharing scenarios. Between 20.1% (Carr) 23.9% (SoCal) stated that trust in others substantially increased.	neighborhood networks (e.g., phone trees, neighborhood associations), social neighborhood events (e.g., block parties), preparedness events (e.g., community meetings, training), and disaster-specific neighborhood groups (e.g., Community Emergency Response Teams (CERTs)). Some trust/compassion building strategies, such as developing community carpools, could function under both normal conditions and disaster conditions. Support for these strategies could come from monetary grants or local fire marshals, chiefs, and boards with knowledge expertise. Developing preparedness guidebooks and brochures would help increase both preparedness and willingness to share, especially if the materials include information on how to share. Agencies should also consider training leaders within neighborhoods on how to connect sharing providers and users. Trustworthy and compassionate leaders and providers are likely rooted in the community and/or have strong social connections.	citizen participation programs (Bihari and Ryan, 2012; Prior and Eriksen, 2013). Social and neighborhood networks (Chamlee-Wright and Storr, 2009a Aldrich, 2012; Dussaillant and Guzman, 2014; Fan et al., 2020) Leadership (e.g., Nakagawa and Shaw, 2004; White and Fu, 2012)
Ensure that community members, including evacuees, can easily volunteer	Past volunteers in disasters were moderately more likely to share for several sharing scenarios. Volunteerism was high for the wildfires as 44.2% (SoCal) and 46.8% (Carr) volunteered. Volunteerism for the wildfires increased by 7.5% (SoCal) and 13.3% (Carr) compared to past volunteerism. Members of a local community organization or group were typically more likely to share for	A significant number of respondents were active volunteers in the wildfires. Given that many individuals also evacuated, agencies should continue to make volunteering easy (e.g., developing volunteering groups, fast signup, guiding emergent behavior), which will help to increase the amount of resources available for response, recovery, and future disasters.	Volunteer mechanisms (Quarantelli, 1984; Drabek and McEntire, 2002; Fernandez, 2007; Starbird and Palen, 2011; Scanlon et al., 2014; Whittaker et al., 2015)
Maintain volunteer networks to keep volunteerism high for the next disaster		Past volunteers were more likely to share under certain circumstances, indicating that volunteer networks could be part of a sharing strategy. Network maintenance may require local agencies to reward assistance through volunteer recognition, communicate with volunteers on a regular basis, and host social gatherings for volunteers.	
Strengthen partnerships with CBO		Some community organizations may be positioned in the local area to provide rapid response in disasters, due to their	CBO partnerships (Sutton and

volunteer networks, which can be called upon in a disaster for transportation and sheltering	several sharing scenarios.	volunteer and supply networks. Members of community organizations can provide needed transportation and sheltering resources through a more trusted organization (instead of through private citizens). Some networks already exist and should be expanded (e.g., American Red Cross, churches), but more local organizations may be more flexible in meeting community needs.	Tierney, 2006; Austin, 2012; Ishiwatari, 2012; Matsuoka et al., 2012; Rivera and Nickels, 2014)
Link local CBOs and volunteer networks with known centers, neighborhoods, and communities with a high proportion of access and functional needs populations	13.0% (SoCal) and 3.2% (Carr) of respondents received a mandatory evacuation order but did not evacuate. Members of a local community organization or group were typically more likely to share for several sharing scenarios. Past volunteers in disasters were moderately more likely to share for several sharing scenarios.	Some individuals continue to remain at home even though they received a mandatory evacuation order. While some individuals may defend their home, others may be unable to leave due to lack of resources and/or low mobility. Local CBOs could provide resources, especially since organization members are more willing to share resources. Agencies may need to first compile a list of areas with functional and access needs populations. Public assets may be able to meet these needs, but CBOs may be well-equipped to aid when necessary.	NGO/CBO strategies for vulnerable populations (Bolin and Stanford, 1998; Drabek and McEntire, 2002; Sutton and Tierney, 2006; Simo and Bies, 2007; Klaiman et al., 2010; Matsuoka et al., 2012; Chandra et al., 2013; Gin et al., 2016)
Increase public resources (e.g., public transit) and/or NGO and CBO resources (e.g., carpools) for areas that previously evacuated from wildfires	Previous evacuees were less likely to share for several sharing scenarios.	Past evacuation experience sometimes decreased willingness to share. Local public transit and emergency management agencies could deploy resources to areas that they previously evacuated. Agencies will need to maintain continuity of knowledge to ensure that previously evacuated areas and fire perimeters are identified and mapped.	Higher capacity transportation resources (Wolshon et al., 2005; Bish, 2011; Swamy et al., 2017; Dulebenets et al., 2019; The City of New Orleans, 2019; Wong et al., 2020)
Minimize safety concerns by matching providers and evacuees	Safety and security concerns were expressed by a significant number of respondents for both	With safety as a primary concern, both providers and users of shared resources may be more comfortable with sharing through established CBOs and volunteer networks. CBO credibility may also	CBO partnerships (Sutton and Tierney, 2006; Austin, 2012;

through established CBOs	transportation and sheltering (non-sharers were especially concerned). Members of a local community organization or group were moderately more likely to share for several sharing scenarios. Respondents were not concerned about the lack of governmental oversight for a shared resource strategy.	increase trust of neighbors and strangers. While local agencies could also match providers and users, CBOs may be better positioned to encourage members and other volunteers to share resources. Private sharing companies often partner with CBOs to provide rides and shelter.	Ishiwatari et al., 2012; Matsuoka et al., 2012; Rivera and Nickels, 2014) Private sector resources (Johnson et al., 2011; White and Fu, 2012; Chapter 3)
Leverage police and fire personnel to communicate the need to share resources and check on neighbors	High police presence on the route increased willingness to share transportation while evacuating for both SoCal and Carr. High pressure from officials to leave somewhat increased willingness to share transportation before evacuation for SoCal. Mean trust of police was higher than trust of neighbors.	Public officials, particularly police and fire personnel, assist in distributing evacuation orders within neighborhoods. Authority figures with subject matter expertise (e.g., fire marshals and firefighters for wildfires) may be highly trusted in disasters, especially if they provide accurate and useful public information. This trust level may allow experts to communicate additional information on how to share transportation and sheltering and check on neighbors during the disaster. Moreover, since police and fire are assisting within neighborhoods, they can communicate directly with sharing providers and users. Other public officials and local politicians can also play a role in communicating sharing needs to the community.	Wildfire response communication strategies (Kumagai et al., 2004; Taylor et al., 2005; Taylor et al., 2007; Stidham et al., 2011; Steelman and McCaffrey, 2013; Steelman et al., 2015)
Set pickup points for shared transportation along major arterial roadways	Respondents stated that two of their primary reservations of sharing were the possibility of a longer evacuation and having to deviate from the evacuation route. Both sharers	With such limited time to evacuate and travel to a destination, evacuees exhibited strong risk aversion to increasing the travel time of their evacuation or deviating from their route. A future shared resource strategy could consider pickup points along major arterial roadways to reduce the need to deviate. These pickup points could also be integrated into a public transit-based response. Not all individuals will be able	Pickup points for evacuations (Abdelgawad et al., 2010; Bish, 2011; Bian and Wilmot, 2017; Qazi et al., 2017; The City of New Orleans, 2019)

	and non-sharers were highly concerned.	to travel to these pickup points so some vehicles will have to provide point-to-point service to ensure safe and equitable outcomes.	
Increase community trust and compassion during and after the disaster to increase willingness to share resources	Trust, especially trust of neighbors and strangers, significantly increased willingness to share for most sharing scenarios. Compassion, especially non-selfish compassion and tender compassion, significantly increased willingness to share for most sharing scenarios Between 20.1% (Carr) 23.9% (SoCal) stated that trust in others substantially increased. Several urgency variables (e.g., high visual fire level, high smoke level, high traffic levels and low visibility) increased willingness to share transportation, indicating that sharing can be triggered by the disaster.	While a significant amount of trust/compassion building can occur prior to the disaster, some strategies could be used during or after the disaster. Based on the significance of urgency variables, disasters may help to trigger sharing behavior. Local agencies can encourage this behavior by using community-building language (e.g., positive and encouraging press releases focused on community strength and resilience), communicating directly with local neighborhood associations, leaders, or CERTs, and encouraging sharing response – especially transportation pickups – in high urgency neighborhoods with proximity to the fire. Agencies can also offer continuing information on community needs throughout the wildfires and recovery, including how residents can supply long-term sheltering or transportation for evacuees to gather basic necessities or access health care.	Wildfire response communication strategies (Kumagai et al., 2004; Taylor et al., 2005; Taylor et al., 2007; Stidham et al., 2011; Steelman and McCaffrey, 2013; Steelman et al., 2015)

4.6) Study Limitations

It is important to note that our study design has several limitations. First, our survey has a self-selection bias, since respondents opted into the study. The online survey only reached individuals with Internet access, causing significant under sampling of technology non-users. This undersampling, while not problematic for modeling willingness to share, likely causes an overestimation of sharing resource capacity. We attempted to reduce these limitations by distributing the survey across multiple agencies with varying captured populations. We also received assistance from local CBOs and news organizations to distribute the surveys more broadly. To reduce self-selection and non-response bias, we also offered an incentive via a random drawing. Incentives are designed to encourage higher response across the general population, who may be less likely to participate in an incentive-absent survey compared to captive individuals with a high interest in the topic. Still, both survey samples skew female, white, higher-income, higher education, and higher vehicle ownership. Consequently, this likely overestimates the available capacity of sharing economy resources. This sampling limitation also prevents us from knowing how vulnerable populations make choices. Indeed, willingness to share is likely overestimated, as those without vehicle access (who were under sampled) are unable to provide transportation in disasters. In our case, vulnerable populations could be either providers or users of shared resources. We attempted to use less precise variables by homogenizing groups in the sample that could still denote vulnerable populations (e.g., white vs. non-white; households with an individual with a disability vs. household without; high-income vs. medium-income vs. low-income). However, we generally found that these variables were not significant in our modeling, indicating that future work is necessary to build consensus.

We also recognize that some limitations exist in the design of the survey instrument, which included over 150 questions and may have led to severe survey fatigue. Future work is needed to reduce the number of survey questions to key variables or split the instrument into separate surveys. For the sharing economy questions, respondents may not have been able to conceptualize sharing resources in a disaster or during recovery efforts. While we asked respondents about their evacuation experience, characteristics of their choices, and sociodemographics, we did not ask respondents about their social networks. The strength of social networks could be a key indicator for willingness to share. We asked respondents about their social connections via community groups and volunteering, which serve as reasonable proxies for social networks.

We note several modeling limitations with our chosen binary structure. We attempted to model choice through several multinomial choice structures but found that the most distinctive difference in behavior was between extremely likely sharers and all other responses. However, a future research direction would be to take advantage of the ordering of responses through an ordered logit model. Moreover, the choices in these scenarios are likely to be correlated. Given this potential correlation structure, future research could also attempt to model these choices jointly, taking advantage of nested, portfolio choice, or latent class choice models to determine any potential joint preferences. We also did not find any benefit in a mixed logit formulation. This negative result may not appear in other datasets and should continue to be tested in other situations.

Finally, we acknowledge that the sharing economy is just one tool for evacuating individuals and would likely be a small fraction of mode and shelter choices. However, we stress that any tool that could increase the amount of resources available in evacuations deserves exploration, especially if these resources increase compliance, decrease congestion, and ensure more equitable evacuations.

4.7) Conclusions

In this paper, we explored wildfire logistics and the feasibility of the sharing economy for wildfire evacuations using survey data from the 2017 December Southern California Wildfires and the 2018 Carr Wildfire. For wildfire logistics, we found low non-compliance rates, a significant number of multi-vehicle evacuations, and high usage of family and friends for sheltering. Public shelter use and peer-to-peer services were low for both wildfires, and most evacuations were within county. We also found evidence of spare capacity across evacuating vehicles for both wildfires.

Through four sharing scenarios, survey respondents were somewhat likely to share shelter at cost, moderately likely to share shelter for free and transportation before an evacuation, and very likely to share transportation while evacuating. A significant number of wildfire respondents recently volunteered and perceived trust increases in their community following the wildfires. Through eight binary logit models, we found a nuanced story regarding willingness to share that was highly dependent by scenario and wildfire. We found a strong presence of trust and compassion in increasing willingness (confirming our original hypothesis), moderate impact of evacuation urgency, and weaker impact of evacuation circumstances and demographics. Moreover, we found that non-sharers had considerably more concerns/reservations than sharers, with the exception of transportation during the evacuation, which suggests that concerns will need to be addressed to retain a higher likelihood of sharing.

We conclude that a sharing economy strategy is feasible for wildfire evacuations, albeit with some important limitations including sharing reservations and sometimes low willingness depending on the scenario. We recommend that future sharing economy strategies should build trust and compassion prior to disasters within neighborhoods, CBOs, and volunteer networks, but they should also leverage communication mechanisms to trigger trusting and compassionate responses during an evacuation. We recommend that future work, such as Rezende et al. (2016) and Sadri et al. (2018), continue to assess social capital and social networks for disruptive events. Social media in disasters (for example as studied in Ukkusuri et al., 2014 and Roy et al., 2020) may be a possible mechanism to bridge social networks and a sharing economy strategy, while work related to social capital indices for disaster (Cox and Hamlen, 2015) could identify communities able to share resources. Future work should also continue on the demand side of the sharing economy, such as the work conducted by Borowski and Stathopoulos (2020), especially by asking evacuees about their mode choice in previous events. We hypothesize that sharing can be developed pre-disaster, but it can also be activated, guided, and promoted by agencies during a disaster. While the sharing economy may remain an evacuation tool for only a small fraction of the community, an increase in resources would help more citizens access transportation and sheltering. Future work should continue to build upon this research through the exploration and development of a practice-ready framework for building trust in the community as part of disaster preparedness, which addresses barriers to resource sharing.

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4.9) Appendix

Table A1: Demographic Characteristics of Survey Respondents

	2017 Southern California Wildfires	2018 Carr Wildfire
Individual Characteristics	*n=226*	*n=284*
Gender		
Male	26.1%	30.3%
Female	73.9%	69.7%
Age		
18-24	2.7%	2.8%
25-34	17.7%	12.7%
35-44	15.0%	19.0%
45-54	19.0%	22.9%
55-65	26.5%	19.7%
65+	19.0%	22.9%
Race		
Asian	2.7%	1.1%
Black or African American	0.4%	0.0%
Mixed	7.5%	3.5%
Native American/Alaska Native	0.4%	1.4%
Pacific Islander	0.9%	0.0%
White	81.4%	90.8%
Other	4.0%	0.0%
Prefer not to answer	2.7%	3.2%
Ethnicity		
Hispanic	11.1%	5.3%
Not Hispanic	76.1%	87.3%
Prefer not to answer	8.8%	7.4%
Education		
Less than high school	0.0%	0.7%
High school graduate	0.9%	4.9%
Some college	15.9%	23.2%
2-year degree	5.8%	12.0%
4-year degree	41.2%	27.8%
Professional degree	28.3%	27.5%
Doctorate	8.0%	3.9%
Prefer not to answer	0.0%	0.0%
Employment		
Employed full time	57.1%	47.9%
Employed part time	11.9%	10.9%
Unemployed looking for work	2.2%	2.8%
Unemployed not looking for work	2.7%	4.2%
Retired	22.1%	26.1%
Student	2.2%	1.8%
Disabled	1.3%	2.8%
Prefer not to answer	0.4%	3.5%
Primary Mode of Transportation		

Drive alone using a car, SUV, pickup, or van	87.6%	92.6%
Carpool/vanpool	2.2%	1.4%
Rail (e.g., light/heavy, subway/metro, trolley)	0.9%	0.0%
Bus	1.8%	0.0%
Motorcycle/scooter	0.9%	0.4%
Bicycle	0.9%	0.7%
Walk	0.4%	0.0%
Shuttle service	0.0%	0.4%
Work from home	1.8%	1.4%
Other	0.9%	2.8%
Prefer not to answer/No answer	2.7%	0.4%
Previous Evacuee		
Yes	35.3%	31.0%
No	64.7%	69.0%
Previous Wildfire Experience		
Yes	93.4%	89.1%
No	6.6%	10.9%
Mobile Phone Type		
Do not own a mobile phone	2.7%	3.2%
Own a typical mobile phone (non-smartphone)	5.3%	3.9%
Own a smartphone	92.0%	93.0%
Access to Internet at Home		
Yes	98.7%	97.2%
No	1.3%	2.8%
In-Vehicle or Smartphone Navigation		
Yes	79.6%	78.2%
No	20.4%	21.8%
Household Characteristics	*n=226*	*n=284*
Displacement after Wildfire		
Same Residence	88.9%	87.0%
Displaced	10.6%	13.0%
No answer	0.4%	0.0%
Length of Residence		
Less than 6 months	5.8%	3.2%
6 to 11 months	4.9%	5.3%
1 to 2 years	12.4%	13.7%
3 to 4 years	14.6%	9.5%
5 to 6 years	7.1%	7.7%
7 to 8 years	5.3%	5.3%
9 to 10 years	4.9%	6.0%
More than 10 years	45.1%	49.3%
Residence Structure		
Site build (single home)	73.9%	91.2%
Site build (apartment)	19.5%	4.2%
Mobile/manufactured home	6.2%	4.6%
Prefer not to answer	0.4%	0.0%

Homeownership		
Yes	67.3%	81.3%
No	29.6%	17.3%
Prefer not to answer	3.1%	1.4%
Live in Cal Fire Very High or High Risk Area*		
Yes	38.1%	37.7%
No	28.8%	35.2%
I don't know	33.2%	27.1%
Household Characteristics		
Household with Disabled	14.2%	18.7%
Household with Children	25.2%	35.2%
Household with Elderly	28.3%	31.3%
Households with Pets	63.7%	81.7%
Household Income (Prior Year)		
Less than $10,000	0.4%	0.7%
$10,000 - $14,999	1.3%	3.9%
$15,000 - $24,999	2.2%	2.8%
$25,000 - $34,999	2.2%	5.6%
$35,000 - $49,999	6.2%	9.5%
$50,000 - $74,999	14.6%	17.6%
$75,000 - $99,999	11.5%	14.8%
$100,000 - $149,999	21.2%	19.7%
$150,000 - $199,999	13.3%	5.6%
More than $200,000	14.2%	8.1%
Prefer not to answer	12.8%	11.6%
Vehicle Ownership/Leasing		
0 vehicles	0.9%	0.0%
1 vehicle	23.0%	15.8%
2 vehicles	46.5%	41.5%
3+ vehicles	29.7%	42.6%
County of Residence	*n=226*	*n=284*
Ventura	43.8%	
Santa Barbara	41.6%	
Los Angeles	13.3%	
Other California	1.3%	
Shasta		94.0%
Other California		2.5%
Non-California		3.5%

Note: Percentages may not add to 100% due to rounding
*Very High or High fire severity zone as defined by the California Department of Forestry and Fire Protection (Cal Fire)

Table A2: Additional Evacuation Logistics

	2017 Southern California Wildfires	2018 Carr Wildfire
Evacuees Only	*n=175*	*n=254*
Evacuation Travel Time		

Less than 30 min.	13.1%	5.1%
30 min. – 59 min.	25.7%	24.0%
1-1.99 hours	22.9%	23.2%
2-2.99 hours	13.7%	17.3%
3-3.99 hours	6.3%	10.2%
4-4.99 hours	6.9%	5.1%
5-9.99 hours	6.3%	6.3%
10 hours or more	5.1%	7.9%
No answer	0.0%	0.8%
Usage of GPS for Routing		
Yes, and followed route	18.3%	7.5%
Yes, but rarely followed route	4.6%	5.5%
No	77.1%	87.0%
Multiple Destinations		
Yes	41.7%	48.4%
No	58.3%	51.6%
Length Away from Home		
Less than 1 day	4.6%	1.2%
1-2 days	22.9%	11.8%
3-4 days	24.6%	18.1%
5-6 days	14.3%	22.8%
7-8 days	7.4%	23.2%
9-10 days	5.7%	7.1%
11-14 days	9.1%	3.9%
15-21 days	4.6%	4.3%
More than 21 days	6.9%	7.5%

Note: Percentages may not add to 100% due to rounding

Table A3: Weighted Concerns/Reservations for 2017 Southern California Wildfires

	S1-Shelter-Cost		**S2-Shelter-Free**	
Concerns/Reservations About Sheltering an Evacuee (Full Sample)	Sharers	Non-Sharers	Sharers	Non-Sharers
Not having enough water and/or food	9%	33%	16%	38%
Uncertainty about one's own safety or security	17%	82%	27%	76%
Having to interact with a stranger	11%	55%	19%	54%
Feeling responsible for the additional house guest(s)	15%	71%	26%	69%
Having to drive the individuals around	2%	16%	8%	19%
Disruption of everyday tasks	11%	66%	23%	57%
General dislike of hosting	4%	30%	10%	28%
Not having enough space for the additional guest(s)' belongings	5%	35%	12%	39%
No government oversight	2%	10%	3%	7%

Concerns/Reservations About Transporting an Evacuee (Evacuees Only)	S3-Transport-Before		S4-Transport-During	
	Sharers	Non-Sharers	Sharers	Non-Sharers
Having to deviate from an evacuation route	26%	50%	43%	36%
Adding extra time to the evacuation	41%	69%	66%	48%
Not having enough fuel	15%	21%	22%	14%
Not having enough water and/or food	5%	9%	9%	8%
Uncertainty about one's own safety or security	33%	54%	51%	40%
Having to interact with a stranger	16%	31%	26%	28%
Feeling responsible for the additional passenger(s)	34%	55%	50%	39%
Having to drive the individuals for a long period of time	15%	29%	24%	21%
Not having enough space for the additional passenger'(s) belongings	41%	66%	60%	49%
No government oversight	4%	7%	6%	7%

Table A4: Weighted Reservations for the 2018 Carr Wildfire

Concerns/Reservations About Sheltering an Evacuee (Full Sample)	S1-Shelter-Cost		S2-Shelter-Free	
	Sharers	Non-Sharers	Sharers	Non-Sharers
Not having enough water and/or food	12%	40%	16%	32%
Uncertainty about one's own safety or security	14%	73%	31%	74%
Having to interact with a stranger	8%	42%	21%	47%
Feeling responsible for the additional house guest(s)	12%	63%	23%	56%
Having to drive the individuals around	5%	19%	9%	20%
Disruption of everyday tasks	9%	49%	21%	49%
General dislike of hosting	3%	23%	11%	27%
Not having enough space for the additional guest(s)' belongings	11%	51%	17%	38%
No government oversight	1%	6%	3%	5%

Concerns/Reservations About Transporting an Evacuee (Evacuees Only)	S3-Transport-Before		S4-Transport-During	
	Sharers	Non-Sharers	Sharers	Non-Sharers
Having to deviate from evacuation route	27%	36%	45%	22%
Adding extra time to the evacuation	40%	51%	66%	31%
Not having enough fuel	16%	16%	21%	8%

Not having enough water and/or food	7%	6%	7%	3%
Uncertainty about one's own safety or security	45%	51%	66%	37%
Having to interact with a stranger	14%	19%	25%	15%
Feeling responsible for the additional passenger(s)	22%	28%	38%	20%
Having to drive the individuals for a long period of time	10%	15%	18%	10%
Not having enough space for the additional passenger'(s) belongings	35%	50%	61%	33%
No government oversight	1%	1%	2%	1%

Note: The publication in the International Journal for Disaster Risk Reduction includes survey questions there were used for data collection. That file can be downloaded at: https://www.sciencedirect.com/science/article/abs/pii/S2212420920314023

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Chapter 5: Can Sharing Economy Platforms Increase Social Equity for Vulnerable Populations in Disaster Response and Relief? A Case Study of the 2017 and 2018 California Wildfires

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ABSTRACT
Ensuring social equity in evacuations and disasters remains a critical challenge for many emergency management and transportation agencies. Recent sharing economy advances – including transportation network companies (TNCs, also known as ridehailing and ridesourcing), carsharing, and homesharing – may supplement public resources and ensure more equitable evacuations. To explore the social equity implications of the sharing economy in disasters, we conducted four focus groups (n=37) of vulnerable populations impacted by California wildfires in 2017 or 2018. To structure these data, we employed the **S**patial **T**emporal **E**conomic **P**hysiological **S**ocial (STEPS) equity framework in an evacuation context. We contribute to the literature by: 1) summarizing the focus groups and their opinions on the sharing economy in evacuations; 2) capturing wildfire evacuation obstacles through the STEPS transportation equity framework; and 3) linking STEPS and focus group results to explore the future potential of shared resources. Using STEPS, we also expand our shared resource exploration to 18 vulnerable groups.

We found that all focus groups were highly concerned with driver availability and reliability and the ability of vehicles to reach evacuation zones, not necessarily safety and security. Each group also expressed specific limitations related to their vulnerability. For example, individuals with disabilities were most concerned with inaccessible vehicles and homes. Using the STEPS framework, we found that while multiple vulnerable groups could gain considerable benefits from shared resources, 10 of the 18 groups experience three or more key challenges to implementation. We offer several policy recommendations to address equity-driven planning and shared resource limitations.

Keywords: Evacuations, Sharing Economy, Transportation Network Companies, Homesharing, Social Equity, Vulnerable Populations

5.1) Introduction

In recent years, the United States (U.S.) has been severely impacted by multiple large-scale disasters, requiring evacuations to safeguard residents. Multiple large and destructive hurricanes in 2017 and 2018 including Hurricanes Harvey, Irma, Maria, Florence, and Michael led to the evacuation of millions of people. Fast-moving wildfires in California including the October 2017 Northern California Wildfires and the December 2017 Southern California Wildfires, along with the Mendocino Complex, Carr, Camp, Hill, and Woolsey wildfires, led to the evacuation of thousands. Even with the rise in disasters, many transportation and emergency management agencies remain unprepared to transport and shelter all citizens in disasters, mostly due to a lack of necessary resources and assets. Consequently, some citizens – particularly those most vulnerable such as the carless – are unable to evacuate in a disaster. Other vulnerable groups including older adults, individuals with disabilities, low-income households, and non-English speaking households, struggle to receive information about evacuations and find adequate transportation and sheltering. Recent research has found that one third of the 50 largest cities in the U.S. do not have an evacuation plan (Renne and Mayorga, 2018). Moreover, of those cities that do have a plan, just half mention carless or vulnerable populations (Renne and Mayorga, 2018). To ensure equitable evacuations, new strategies will need to be employed to increase assets and safely transport and shelter vulnerable populations.

Along with an increase in disasters and evacuations, the sharing economy – consisting of Internet-based transactions to share and obtain goods – has grown rapidly in the past decade. This growth has been most apparent in the sharing economy companies in transportation (e.g., Uber, Lyft, Zipcar) and hospitality (e.g., Airbnb, VRBO). Since Hurricane Sandy in 2012, many of these companies have been actively involved in disaster response and relief (Wong et al., 2018; Chapter 3). Recent research has also found that individual citizens are moderately willing to offer shared resources to evacuees for future disasters (Chapter 3). Given the rise of the sharing economy in evacuations and encouraging research on its feasibility, we hypothesize that shared resources – from private companies or private citizens – could be one tool to develop more equitable evacuations.

In this paper, we address both the equity benefits and limitations of the sharing economy in evacuations. We expand on focus group results presented in Wong and Shaheen (2019) to emphasize the research in the broader evacuation and equity literature and employ the **S**patial **T**emporal **E**conomic **P**hysiological **S**ocial (STEPS) framework. We guide this research through several questions including:

1. What social equity challenges do individuals face in evacuations?
2. What is the opinion of vulnerable groups on the sharing economy under disaster conditions?
3. What are the key benefits and limitations of the sharing economy for specific vulnerable groups? Are shared resources more feasible for certain groups?

We answer these questions through results from four vulnerable population focus groups of individuals impacted by California wildfires in 2017 or 2018, which we conducted from August 2018 to March 2019; an application of the STEPS transportation equity framework (Shaheen et al., 2017); and an exploration of the equity implications of shared resources. We first present a literature review focused on social equity in evacuations, providing the framing of how a shared resource strategy could improve social equity challenges. We then describe our research methodology and its limitations. Next, we present the results of the four vulnerable population focus groups. We then link the focus groups and STEPS framework to present the benefits and limitations of shared resources across 18 different vulnerable groups. Finally, we offer policy recommendations for agencies to improve social equity for shared resources in evacuations.

5.2) Literature Review

5.2.1) The Sharing Economy and Shared Resources

With improved technology and communication ability, the sharing economy has grown rapidly in the past 10 years. It consists of peer-to-peer (P2P) or business-to-consumer (B2C) transactions via the Internet where goods and services are shared and obtained. Enabled through information and communication technologies (ICT), P2P and B2C services are transforming the built environment and how individuals interact with goods and services. However, several key challenges to shared behavior and engaging with the sharing economy include: business model sustainability, labor exploitation, limited consumer protection, disregard of regulation, and social equity challenges.

5.2.2) Shared Mobility, Shared Housing, and Social Equity

With the rise of companies, such as Airbnb and HomeAway, homesharing has become a major sector of the sharing economy. Typically, these services are used as short-term accommodations when traveling and offer a lower cost option to more traditional hospitality services, such as hotels. Recent research has also begun to look at homesharing impacts within the sharing economy. For example, research has found that Airbnb has had a causal and negative impact on hotel revenue, particularly on lower-priced hotels (Byers et al., 2013; Zervas et al., 2017).

Shared mobility is an innovative transportation strategy where users are typically able to access shared vehicles, bicycles, or other modes on an as-needed basis (Shaheen et al., 2016). It employs variable cost mechanisms that can offer individuals greater choice, lower costs, and increased convenience for transportation. Recent literature has provided an overview of many of these different shared mobility options, such as transportation network companies (TNCs, also known as ridehailing and ridesourcing), carsharing, ridesharing, and bikesharing (e.g., Shaheen et al., 2016; Rayle et al., 2016; Shaheen and Cohen, 2013; Chan and Shaheen, 2012; Furuhata et al., 2013; Shaheen et al., 2010) and the impacts of these options on cities and transportation (Meyer and Shaheen, 2017). A list and description of many shared mobility options can be found in Shaheen et al. (2016).

Since the emergence of the sharing economy, several studies have addressed the potential for shared mobility to serve as a more equitable transportation mode. Studies including Rauch et al. (2015) and Shaheen et al. (2017) have proposed that shared mobility is a pathway to increase accessibility, reduce auto travel costs, and allow more flexible travel patterns. Use of shared mobility as a strategy for addressing transportation equity concerns also extends into policy and planning practice (Shaheen et al., 2017). Shaheen et al. (2017) note the limitations that can arise from shared mobility in serving low-income, older adult, and disabled populations. The lack of technology access – or the digital divide – remains a primary barrier for equitable shared mobility.

Prices for shared mobility also remain high under many circumstances, and vehicles are often not well-equipped for those with disabilities and may not provide equitable access in lower-income and/or lower-density neighborhoods. Further, there has been ongoing research on shared mobility and sheltering regarding discrimination (Ge et al., 2016; Edelman et al., 2017). Equity issues in consumer protection, privacy, safety, and worker rights also persist.

5.2.3) Social Equity and Resource Deficiencies in Evacuations

Social equity has also been a critical area of concern in evacuations. The lack of equitable evacuation and emergency planning was most acutely clear during Hurricane Katrina in New Orleans, Louisiana in 2005 (Wolshon, 2002; Renne, 2006). Many of these equity lessons learned are summarized in Litman (2006). Hurricane Katrina exposed severe resource deficiencies for some vulnerable populations; estimates of 127,000 to 300,00 people in the New Orleans Metropolitan area did not have access to reliable transportation (Wolshon, 2002; Boyd et al., 2009). An estimated 100,000 people did not evacuate prior to Hurricane Katrina and required transportation assistance following landfall (Boyd et al., 2009). Consequently, New Orleans now offers emergency transportation to carless individuals through its city-assisted evacuation plan, which maps pickup points and leverages city assets such as buses (The City of New Orleans, 2018). However, New Orleans remains an outlier for planning for vulnerable populations, as noted in Renne and Mayoraga (2018). More work is also needed to assess how vulnerable populations would make choices, such as Sadri et al. (2014) for mode choice. One complication of the disaster planning process, however, is that the definition of a vulnerable population is variable based on the state, region, and city (Turner et al., 2010). Developing effective communication strategies for evacuation orders and available resources presents a challenge given the diversity of vulnerable groups and how they are defined. Moreover, frameworks on equity through the lens of social vulnerability (see Cutter et al., 2003 for an overview) sometimes cover both social and place inequality. These different dimensions of inequality require a more holistic understanding of the barriers faced by vulnerable populations in evacuations. Comprehensive reviews of the social equity literature in disaster relief can be found in Perry (1987), Fothergill et al. (1999), Cahalan and Renne (2007), Sorensen and Sorensen (2007), Renne et al. (2008), Sanchez and Brenman (2008), Renne et al. (2009), and Rodriguez et al. (2017).

5.2.4) Recent Social Equity and Resource Deficiencies in Wildfire Evacuations

Recently, a series of wildfires in California have led to mass evacuations, devastating damage, and tragic loss of life. In many cases, the speed of wildfire quickly overcame evacuees, and governments had difficulty deciding where and when to issue evacuation orders and how to manage transportation systems during the evacuation (Watkins et al., 2017; Lewis et al., 2018; Nicas et al., 2018). These wildfires also impact areas along the urban-wildland interface (WUI), which is the zone of land that runs alongside unoccupied wildland and human development. Often, communities along the WUI have few transportation options, and most citizens had to rely on personal vehicle to evacuate. In several cases, smaller public transit agencies including Sonoma-Marin Area Rail Transit (SMART), Vine Transit, and the Santa Rosa CityBus were able to assist in evacuating several hundred evacuees in the October 2017 Northern California Wildfires (SMART Train, 2017; Napa Valley Register, 2017; ABC7, 2017). For the 2017 December Southern California Wildfires, Gold Coast Transit and Santa Barbara Metropolitan Transit District were also able to assist in the evacuation of citizens (Gold Coast Transit, 2017; Brugger, 2017). However, for most wildfire evacuees, personal vehicles were the only option available. In addition, individuals impacted by the Carr Fire, Mendocino Complex Fire, and the Camp Fire (all in 2018) had little to no access to public transportation in their area, leaving those without vehicles behind (Nicas et al., 2018).

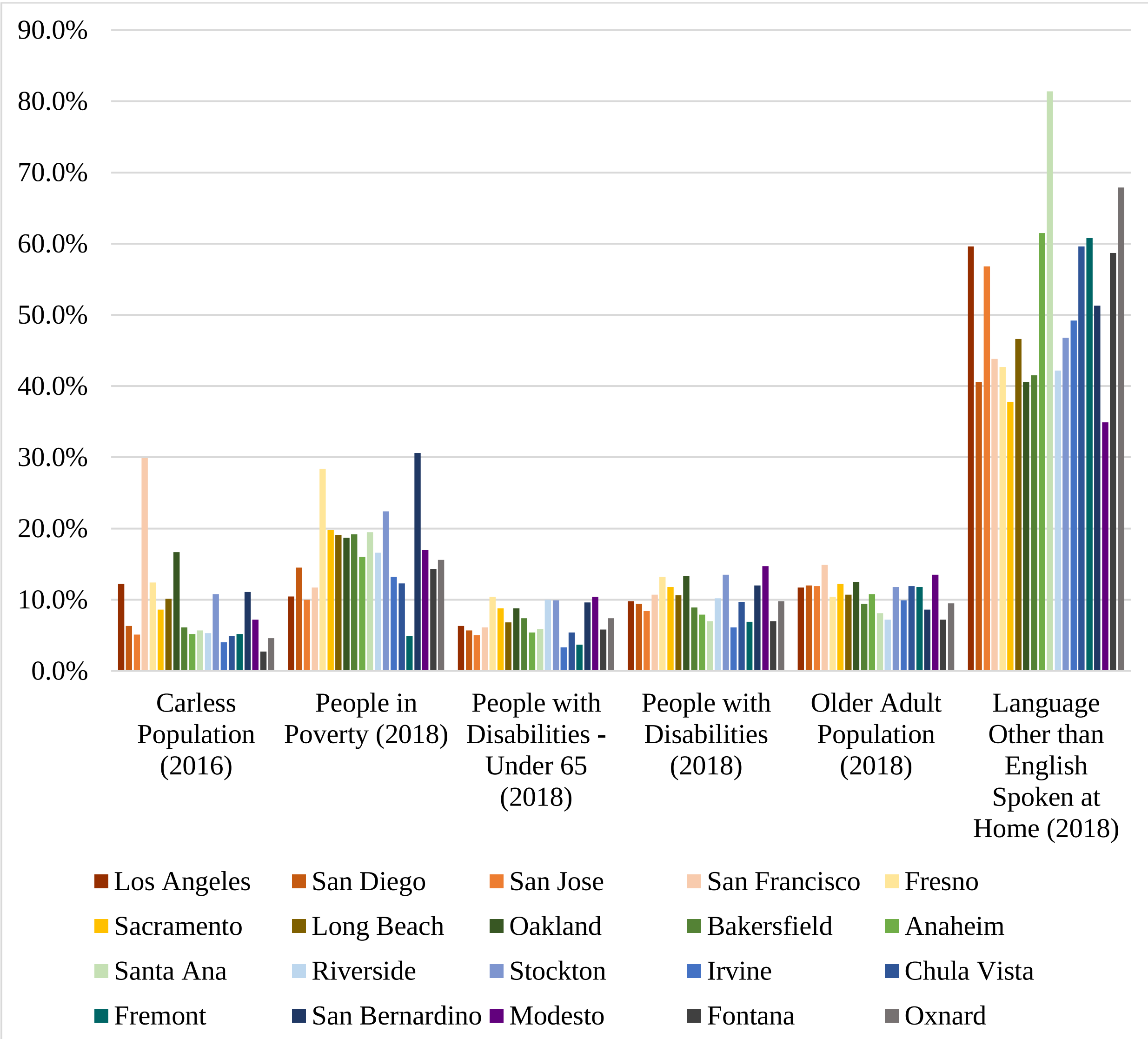
This lack of transportation access is not just an issue for smaller cities in California. As seen in Figure 1, a significant number of individuals in the 20 largest major cities in California are carless (U.S. Census Bureau, 2019). Moreover, multiple California cities also have a high percentage of other vulnerable groups (e.g., low-income, individuals with disabilities, older adult, and non-English speaking). While not all individuals in these cities would be impacted by a wildfire (or series of wildfires), the data indicates severe challenges in successfully evacuating vulnerable groups from even a smaller area. Without an adequate amount of public resources for these vulnerable groups, new strategies must be considered and activated when necessary for future disaster events in California and beyond.

5.2.5) A Sharing Economy Strategy for Evacuations

To address these resource deficiencies and social equity problems, it is possible that the sharing economy and shared resources from companies and private citizens could be leveraged to increase the number assets available in evacuations. While research has identified a number of benefits to this strategy (e.g., increasing compliance, quickening the evacuation process, and serving vulnerable populations), limitations still persist regarding the liability, cost, and structure of the strategy (Wong et al., 2018; Chapter 3). Li et al. (2018) produced a comprehensive study of the evacuation feasibility of DiDi, a TNC based in China, and also acknowledges notable sharing economy limitations. This research, along with Wong and Shaheen (2019), offers policy recommendations on how to leverage shared resources. Most recently, research using stated preference data for no-notice evacuations found that a TNC strategy could be extremely effective for highly urgent evacuations (Borowski and Stathopoulos, 2020). The research also offered an extensive commentary on leveraging TNCs in evacuations, explaining the benefits and limitations of the strategy, particularly for more urban areas.

However, work on determining how a shared resource strategy could improve (or hurt) equitable outcomes in evacuation remains severely limited. We build upon research started in Wong and Shaheen (2019) to determine if a shared resource strategy can produce more equitable outcomes for vulnerable populations. Consequently, we contribute to the evacuation literature by: 1) assessing the obstacles faced by individuals in evacuations, 2) offering evidence through focus groups of vulnerable populations on the impacts of shared resource strategies, and 3) providing practice-ready recommendations for agencies to improve equitable outcomes. Through this research, we begin to understand and develop a more equitable shared resource strategy as a possible tool in evacuations and disaster recovery efforts.

Figure 1: Vulnerable Population Percentages for the 20 Largest California Cities (Listed in Order of Population)



5.3) Research Methodology

To assess the obstacles faced by individuals in evacuations, we employed the STEPS transportation equity framework on the dimensions of **S**patial, **T**emporal, **E**conomic, **P**hysiological, and **S**ocial equity. This framework, developed in Shaheen et al. (2017), takes a holistic and theoretical approach to determining the various dimensions of transportation equity. The framework was originally developed for shared mobility, as barriers along the STEPS dimensions were among the most debilitating for using these transportation services. However, the dimensions are easily expandable to other transportation areas, such as evacuation and recovery efforts, as seen in Table 1.

We note that Cutter et al. (2003) developed a framework for social vulnerability across multiple dimensions, while Vink et al. (2014) used some dimensions to quantitatively estimate the number of vulnerable individuals from a flood evacuation. While we recognize the benefits of these frameworks, we employed STEPS to more closely align transportation equity concerns with a narrower evacuation/recovery context. Moreover, the STEPS framework was originally crafted to overcome key deficiencies in identifying barriers to shared mobility, which is the primary transportation area considered in this paper. For this paper, we employed this framework under wildfire evacuations to explore the equity implications for different vulnerable groups. We note that numerous equity implications are consistent across disasters, and this framework can also be applied for other major disasters (e.g., hurricanes).

Table 1: STEPS Equity Framework for Transportation and Wildfire Evacuations

Dimension	Original Definition for Transportation Equity	Application for Wildfire Evacuations
Spatial	Spatial factors that compromise daily travel needs (e.g., excessively long distances between destinations, lack of public transit within walking distance)	Spatial factors that increase risk, increase evacuation distances, decrease routing options, or compromise evacuations (e.g., single exit routes, high risk fire zones, lack of public transit within walking distance, low proximity to resources, shelters located far away)
Temporal	Travel time barriers that inhibit a user from completing time-sensitive trips, such as arriving to work (e.g. public transit reliability issues, limited operating hours, traffic congestion)	Travel time barriers that inhibit a user from departing at a reasonable time, reaching a destination at an appropriate time, evacuation time costs that lead to non-compliance, or early returners to impacted areas (e.g., additional mobilization time due to medical needs or packing, minimal communication notification, roadway congestion, rapid fire spreading due to wind, public transit reliability issues, work requirements)
Economic	Direct costs (e.g., fares, tolls, vehicle ownership costs) and indirect costs (e.g., smartphone, Internet, credit card access) that create economic hardship or preclude users from completing basic travel	Direct and indirect costs that create economic hardships or preclude users from evacuating (e.g., hotel/supplies/gasoline costs, vehicle ownership costs, time away from job especially for hourly employees)
Physiological	Physical and cognitive limitations that make using standard transportation modes difficult or impossible (e.g., infants, older adults, and disabled)	Physical and cognitive limitations that make using standard transportation modes or sheltering resources difficult or impossible for specific groups (e.g., vulnerable groups including older adults, individuals with disabilities, homebound individuals, etc.; inability/challenge to receive evacuation information due to visual/auditory disability; needing to use accessible vehicles or shelter)

Social 	Social, cultural, safety, and language barriers that inhibit a user's comfort with employing transportation (e.g. neighborhood crime, poorly targeted marketing, lack of multi-language information)	Social, cultural, safety, and language barriers that inhibit a user's comfort or ability in using transportation or evacuating (e.g., vulnerable groups including racial and ethnic minorities, immigrants, undocumented immigrants, Native American and Indian Tribal governments, etc.; lack of multi-language information on evacuation orders, transportation, and sheltering; discrimination in resource allocation)

We supplement the STEPS framework through four focus groups that we conducted from August 2018 to March 2019 of individuals impacted by three different California wildfires in 2017 or 2018 (Table 2). We found participants through related post-disaster surveys and outreach performed by local agencies, news outlets, and community-based organizations (CBOs). In these focus groups, we met with individuals from vulnerable groups to gain insights on the choices that they made throughout the evacuation process, their current use of the sharing economy, and their opinions on leveraging shared resources for future evacuations. Our goal was to interview a wide range of vulnerable groups affected by different fires to gain a broader perspective on the equity impacts of evacuations and the feasibility of the sharing economy as a strategy to expand resources. While each wildfire had unique characteristics and differing governmental response, all wildfires were fast-moving, required mass evacuations, and impacted citizens living on the WUI.

Table 2: California Wildfire Focus Group Overview

Focus Group Population	Focus Group Eligibility	Wildfire	Number of Participants	Focus Group Location & Date
Older Adult	65 years or older	2017 Oct. Northern California	10	Rohnert Park, California (Aug. 2018)
Individuals with Disabilities	Disability or family member with a disability	2017 Oct. Northern California	10	Rohnert Park, California (Aug. 2018)
Low-Income	2017 household income below $40,000	2017 Dec. Southern California	8	Ventura, California (Aug. 2018)
Spanish-Speaking	Speak Spanish in the household	2018 Mendocino Complex	9	Lakeport, California (Apr. 2019)

We specifically developed these groups to collect information from vulnerable populations who experience additional challenges and barriers in an evacuation. We considered conducting research using a survey to increase size. However, we found that our associated surveys on individuals impacted by wildfires severely undersampled vulnerable populations and diminished any understanding of how vulnerable populations would interact with shared resources. In addition, a survey method for vulnerable individuals using in-person, mail, phone, and online communication would have required significant monetary resources that were unavailable to the team. These focus groups were conducted in direct response to the undersampling in our wildfire surveys.

We defined each focus group population to broadly reflect the vulnerable groups most impacted by the chosen wildfires (2017 Northern California Wildfires, 2017 Southern California Wildfires, 2018 Mendocino Complex Wildfire). Individuals in three of the focus groups were first contacted through their participation in related surveys for the 2017 Northern California and 2017 Southern California Wildfire surveys. The groups (each with a maximum of 10 people) were filled first using the survey participants and then with additional participants found through local partner agencies. We worked with partner agencies to identify both focus group locations and participants. These partners were contacted based on their experience with the wildfires (e.g., local emergency management and transportation agencies), ability to reach a wide population (e.g., news media), or work with vulnerable populations (e.g., community-based organizations and non-governmental organizations). Partner agencies were encouraged to advertise the focus groups across online platforms and in-person connections. We also provided a web-based and telephone-based recruiting tool for participants to sign up. We formed the Spanish-speaking focus group for the Mendocino Complex Wildfire solely through partnering agencies, since we did not distribute a prior survey there (as we did in the other three focus groups). All participants were incentivized with a $100 gift card and the Spanish-speaking focus group was conducted only in Spanish.

5.4) Study Limitations

This study leverages insights from four qualitative focus groups, which represent a small sample of the overall population. Thus, these individuals are not representative of the general population or even the subset vulnerable group. The focus groups exhibit a self-selection bias as individuals opt into the study. Individuals may have been less forthcoming within the focus group context, particularly given that the researcher was present and focus group members may have learned about the group via communication from a governmental agency. For some groups and especially the Spanish-speaking focus group, the lack of knowledge of sharing economy resources or the ability to use resources led to few responses. We also acknowledge that a sharing economy strategy for the California wildfires context may not be applicable for wildfires in other geographies, let alone different hazards. We strongly recommend that research and strategies for improving equitable outcomes is highly localized, as demographic characteristics differ greatly even between neighborhoods. Different hazards also pose different equity challenges. The STEPS framework, while used here in the wildfire context, can be extended for other disasters (e.g., hurricanes, tornados) to more clearly identify transportation equity dimensions. We also note that the list of vulnerable groups, while extensive, does not fully encompass all individuals (e.g., children, incarcerated individuals). We decided to leave these individuals out of the sharing economy analysis as they would be unable to participate solely in such a strategy. We also do not provide a full overview of other limitations of the sharing economy (reviews in Wong et al., 2018; Li et al., 2018; Borowski and Stathopoulos, 2020; and Chapter 3). For example, communication and power outages could severely hamper matching of individuals for rides or shelter.

Another important limitation of this study is the sample size of only four focus groups. While we achieved a focus group size (between 4 and 12 participants) that is consistent with literature (Carlsen and Glenton, 2011), we likely did not reach saturation of themes and topics for each specific demographic. Empirical research has found that between five (Coenen et al., 2012) to eight (Kirchberger et al., 2009) focus groups are needed to achieve data saturation (i.e., point in data collection when little to no new information is provided, see Guest et al., 2006 for additional overview). Literature has also found that for a homogenous set of participants, 80% of themes could be discovered within two or three focus groups (Guest et al., 2017). However, we note that our focus groups were not homogenous, and we intentionally constructed our groups using different vulnerable populations. This diminishes our ability to make definitive conclusions about each specific vulnerable population.

Despite this limitation, the groups still provided insights on the equity implications of the sharing economy, and more thematic saturation of the sharing economy in evacuations across a group of individuals impacted by wildfires may have been reached. We also note that we were unable to conduct more focus groups due to study resource constraints, as well as identifying enough research subjects. Indeed, only the older adult and individuals with disability focus groups had two and three alternates, respectively. These low numbers also occurred despite considerable outreach to at least five agencies and CBOs per focus group. The limitation also speaks to the broader challenge of recruiting vulnerable populations in research, particularly during recovery periods after disasters. Given our limited resources, we chose to recruit a variety of vulnerable populations to explore more general themes on how shared resources could be beneficial (or problematic) in evacuations. Our design was also guided by the challenge that vulnerable groups are often not represented or accounted for in the disaster or emergency planning process (as noted in the literature review). Overall, since each focus group is not representative of the related vulnerable group, additional research for each vulnerable group will be needed to assess generalizability. However, we note that the purpose of focus groups was not to achieve generalizability, rather it was to uncover possible themes, opinions, and discussions that could serve as a stepping stone for future work on social equity and sharing economy strategies.

Finally, we acknowledge that most focus group participants had never used TNCs or homesharing for evacuation/recovery purposes. This limitation is largely a result of the relatively new presence of the sharing economy, the lack of sharing economy pilots in disaster, and the somewhat limited overlap of company service areas and disasters. We did not specifically seek out focus group participants who had used the sharing economy during the wildfires, as we would have been unable to find enough participants. Consequently, this diminishes the thought-experiment of asking participants to discuss how the sharing economy could be used in an evacuation. However, most participants either had experience or knowledge of TNCs and/or homesharing under normal conditions that allowed them to make more informed opinions. The Spanish-speaking group, with very limited experience, did not thoroughly discuss how companies could assist, but instead it focused on community members helping other community members.

5.5) Focus Group Results

We conducted four focus groups with different vulnerable groups – older adults, individuals with disabilities, low-income individuals, and Spanish-speaking individuals– across several California wildfires from August 2018 to March 2019. We note that individuals in these groups often overlap (i.e., an older adult with a disability), but we encouraged individuals to focus on their specified group’s barriers. As noted in Table 3, most participants across groups evacuated from their respective wildfire and a sizable number also lost their homes. However, not everyone received a mandatory evacuation order, indicating severe communication problems. We found that a majority of older adults and low-income participants used TNCs and homesharing before. This is likely an overrepresentation, particularly for TNCs, as research has found older adults compared to other ages are less likely to take TNCs (Brown, 2018). While experience for low-income individuals is also likely overrepresented, about 24% of Lyft users lived in Los Angeles neighborhoods with a mean income of below $38,000 (Brown, 2018). We also note that some respondents said that their experience with TNCs was more related to shared rides to the airport (e.g., an airport shuttle). In addition, the focus group geographies for the older adult and low-income groups were in areas where TNCs are available and near major cities (i.e., San Francisco, Los Angeles) in which TNCs are heavily used. The older adult group in the San Francisco Bay Area also has access to several other TNC services, including Women Driving Women and Silver Ride (a service for seniors).

No Spanish-speaking participant used TNCs, which is likely due to the rural setting of the Mendocino Complex Wildfire. Low-income individuals had considerable knowledge of Airbnb Open Homes, a program that encourages hosts to provide free shelter to evacuees. Out of the 37 participants, only one evacuee used TNCs during the evacuation while just two used homesharing. One possible explanation for such low usage is that all the wildfires were either in small cities or rural geographies where sharing economy companies are less active. Another explanation is that the cost of shared resources, particularly TNCs, could have made the option cost prohibitive. Finally, participants may have first sought other resources (for example their own vehicles or a public shelter). Indeed, participants may not have known if sharing economy resources would be available, especially since this evacuation/recovery strategy was not promoted or organized by local agencies. We also note that even though few individuals used the sharing economy during an evacuation, individuals still largely had knowledge of the sharing economy, indicating its potential as a resource pool for future disasters.

Table 3: Vulnerable Population Focus Group Characteristics

Focus Group Population	**Older Adult**	**Individuals with Disabilities**	**Low-Income**	**Spanish-Speaking**
Sample Size	**10**	**10**	**8**	**9**
Participant Characteristics				
Evacuated from Wildfire	9	10	6	8
Received Mandatory Evacuation Order	3	4	4	6
Lost Home in Wildfires	4	4	3	0
Sharing Economy Characteristics	N=10	N=10	N=8	N=8*
Used TNCs Before	50%	30%	63%	0%
Used Homesharing Before	60%	50%	50%	38%
Knowledge of Airbnb Open Homes	20%	30%	63%	38%
Used TNCs for Wildfire	0%	10%	0%	0%
Used Homesharing for Wildfire	10%	0%	13%	0%

** One participant had to leave before the sharing economy discussion*

5.5.1) The Sharing Economy in Evacuations

We asked participants to share their opinions of leveraging the sharing economy in evacuations. During this time, we encouraged participants to describe how their evacuation process might be improved or worsened with the sharing economy. Participants were also told to consider both private companies and private citizens as providers of transportation or sheltering resources. The results are summarized in Table 6, which provides the limitations and benefits of TNCs and homesharing, along with the general view of the group on the shared resource strategy. We offer a brief commentary for each group.

Table 6: Benefits and Limitations of Sharing Economy Resources for Evacuations

	Older Adult	Individuals with Disabilities	Low-Income	Spanish Speaking
View of TNCs in Disasters	Mostly negative	Mostly negative	Largely split	Largely split
TNC Benefits	• Real-time mapping and location of drivers • Added resources for relief period • Rides to medical appointments or to gather supplies	• Added resources for relief period • Rides to medical appointments or to gather supplies	• Could be integrated into a larger multi-modal strategy • Assist underserved populations	• Assist carless • Reduce cost of fuel • Increase resources for vulnerable populations, including older adults
TNC Limitations	• Driver availability and reliability • Impact of wildfires on drivers' families • Low willingness of drivers to go into harm's way • Added confusion to the evacuation process • Presence may not substantially increase resource availability	• Vehicles not accessible • Low communication accessibility on platforms • Cost prohibitive • Ride cancellation potential • Lack of driver training, especially for emergency situations	• No driver incentive to assist • Inability to reach evacuation zone • Increase in congestion and travel time • Cost prohibitive • Unavailable to those without smartphones connected to a bank	• Difficult to communicate resources to public • Lack of Spanish translations • Low trust of drivers and companies • Requires knowledge of using the Internet and smartphone
View of Homesharing in Disasters	Somewhat positive	Largely split	Somewhat positive	Somewhat negative
Homesharing Benefits	• Suitable shelter in an evacuation • Allow non-impacted individuals to volunteer	• More comfortable than public shelter • Easier access to food • Allow non-impacted individuals to volunteer	• Escape smoke • Suitable shelter in an evacuation and opportunity to leverage more resources	• More comfortable than public shelters, especially for children and pets • Better access to basic household goods
Homesharing Limitations	• None provided by participants	• Poor accessibility for disabilities • Lack of host training • Poor home layout	• Possible legal consequences regarding short-term rental laws	• Rather stay with friends and family • Low trust of host and strangers • Communication challenges with

		• Lack of necessary medical equipment • Issues with host communication without Internet or smartphones		notifying evacuees in Spanish • Poor credentialing process

5.5.2.1) Older Adults

Overall, older adults did not have a positive outlook on using private companies as a strategy, particularly for sharing rides. Participants were most concerned about drivers and their availability/reliability. This spatial and temporal problem was expanded on, as older adults explained that drivers may also be impacted by the wildfires, may not want to drive into harm's way, and could add confusion to the evacuation process. Still, some older adults explained that mobility platforms could be helpful in a disaster, since the applications could provide real-time mapping and information about the location of drivers. Older adults were more supportive of a government run strategy (social dimension). Moreover, they preferred if drivers were not impacted by the wildfire (spatial dimension) and if costs could be kept low (economic dimension). Finally, they preferred if the sharing economy strategy was implemented during the relief and recovery period, rather than during the evacuation period. Overall, older adults favored a neighborhood network of volunteers that would function similarly to carpooling.

Older adults were more positive about homesharing and mostly found that Airbnb would be a suitable platform to provide sheltering resources in a wildfire. One participant explained that hosting through Airbnb would allow non-impacted community members to volunteer and be part of the recovery process. Airbnb sheltering could also be tax deductible and might encourage more individuals to sign up to host. The shorter discussion and lack of key limitations on homesharing indicates a more favorable view of homesharing in wildfires. Indeed, one older adult used homesharing during the evacuation and found it be a helpful resource.

5.5.2.2) Individuals with Disabilities

The individuals with disabilities group was also negative on leveraging TNCs in an evacuation. Multiple participants explained that sharing economy companies are largely not disability-friendly and do not provide accessibility in the form of communication or vehicles (physiological dimension). They also noted that these services could be cost-prohibitive, especially when compared to lower-cost paratransit. Participants also expressed concern over reliability as some individuals had experienced cancelled rides under normal circumstances (temporal dimension). Individuals with disabilities preferred to support a strategy that created a clear partnership between paratransit and private companies to minimize some of the concerns over reliability and driver training. They also recommended that mobility platform applications be able to document a rider's disability (for both general and evacuation rides) along with any service animal needs (for evacuation rides).

Homesharing limitations largely mirrored concerns with TNCs, specifically on accessibility for disabilities (physiological dimension) and knowledge of hosts (social dimension). Homesharing hosts might not have the equipment or home layout to accommodate an individual with a disability and may not be trained to assist the individual. It would also be challenging to communicate the availability of homes without smartphones or Internet connection. Overall, participants explained that homesharing could be much more comfortable than a public shelter and allow for easier access to food. Individuals with disabilities also noted that homesharing could be a way for concerned community members to volunteer.

5.5.2.3) Low-Income Individuals

Most low-income participants were highly skeptical of using TNCs. Specifically, they did not think that drivers would have an incentive to help in an evacuation (economic dimension) or would be unable to reach evacuees due to blocked off or reversed roads (spatial dimension). Participants were concerned that TNCs might increase congestion and travel times (spatial and temporal dimensions) and that evacuees would be unable to pay, especially without a bank account or smartphone application (economic dimension). Participants strongly believed that any shared mobility strategy should be coupled with a stronger and broader multi-modal strategy. A public transit system, along with shared resources, could be especially helpful for other underserved populations in the area (i.e., Ventura County) such the Hispanic community.

For homesharing, only one participant in the low-income focus group used Airbnb (in this case to escape smoke). However, multiple participants noted that their friends and acquaintances had positive experiences with using the platform for housing following the wildfires. Several participants said that they thought homesharing would be a good platform to leverage for additional resources. A recommendation was also made in reforming short-term rental laws, allowing people to volunteer in an emergency without fear of legal ramifications. The shorter discussion on homesharing indicates that a relief strategy using homesharing is more feasibility and preferred by low-income individuals.

5.5.2.4) Spanish-Speaking Individuals

Most Spanish-speaking participants had little experience with TNCs and homesharing, particularly through private companies. One key emergent theme was that many participants were willing providers of transportation, housing, and food throughout the wildfires, indicating that they were attempting to fill key social dimension equity gaps. Some participants also said that they would be willing to offer a ride to neighbors. The discussion of providing resources is notable since members of the other focus groups concentrated on being receivers of resources.

When asked about benefits and limitations, participants explained that transportation would have been helpful for carless evacuees who had to walk during the evacuations. Sharing transportation might also reduce the cost of fuel and increase resources for other vulnerable populations (e.g., older adults and individuals with disabilities). However, participants expressed distrust of private companies and drivers (social dimension) and had little knowledge of the companies or how they would use the service via a smartphone or the Internet (social and economic dimension). One critical limitation would be the language of communication as Spanish (both written and spoken) would have to be a priority (social dimension).

Trust remained a key theme for homesharing as participants held a generally negative view of a sheltering strategy. Spanish-speaking participants explained that they were more likely to stay with friends and family and would not trust strangers (social dimension). Despite a negative view of public shelters (which may lack Spanish translators, basic household goods, and safety), Spanish-speaking participants did not think that a homesharing strategy through a company (such as Airbnb) would be an adequate substitute in its current form. Indeed, the communication challenges with notifying the public of available housing would diminish the effectiveness of the program. A few participants emphasized that resources were described but only in English for the recent wildfires, making it difficult for Spanish-speakers to find the resources.

5.5.2) Overall Observations

In our discussion with four vulnerable groups, most participants exhibited mixed or negative reactions to TNCs as a shared resource strategy in evacuations. Despite noting a number of limitations (e.g., driver reliability, availability, cost, communication challenges), participants were also quick to make recommendations for a general TNC strategy. All groups noted that any future shared resource strategy for transportation should:

- Plan in advance using well established protocols and by disseminating resource information;
- Build a community-driven approach (neighbors helping neighbors);
- Focus on the recovery period following the evacuation; and
- Train drivers to assist all people in disaster situations.

For homesharing, older adults and low-income participants were more positive while individuals with disabilities and Spanish-speaking participants were more negative. Interestingly, recommendations for a shared resource strategy were highly group specific and were not as fully discussed as TNCs, perhaps due to a greater need to develop transportation strategies. Overall, we note that while many participants had adverse reactions to the sharing economy at the beginning of the conversation, most had more positive thoughts about a shared resource strategy, after offering their own recommendations and improvements (Table 7).

Table 7: Recommendations Provided by Focus Groups for Developing a Sharing Economy Strategy

	Older Adult	Individuals with Disabilities	Low-Income	Spanish-Speaking
General TNC Strategies	• Plan in advance using well-established protocols and by disseminating resource information • Build a community-driven approach (neighbors helping neighbors) • Focus on the recovery period following the evacuation • Train drivers to assist all people in disaster situations			
Group Specific TNC Strategies	• Partner with local governments • Use drivers who live in unimpacted zones • Ensure that costs remain low (no surge pricing)	• Create partnerships with paratransit that could identify and assist individuals with disabilities • Include an option in the application to denote disability or service animal owner	• Create coordination between emergency services and companies to send drivers • Develop multi-modal system that prioritizes public transit with private companies fulfilling first-mile, last-mile	• Provide information on available resources in Spanish • Include credentialing information for drivers to increase trust • Increase emergency education to encourage sharing across the community

Group Specific Strategies for Homesharing	• Offer a tax deduction for providing home to evacuees	• Distribute information about available resources across multiple platforms • Leverage pre-existing senior care and homeless shelter options and expertise	• Reform short-term rental laws to increase supply of homes	• Provide information on available resources in Spanish • Include credentialing information for hosts to increase trust for renters

5.6) Vulnerable Population Matrix – Linking STEPS and Focus Groups

Using the STEPS framework, we constructed Table 8 to reflect vulnerable populations in evacuations. We provide the percent of the California population according to the American Community Survey 2012 to 2016 (five-year estimates) (US Census Bureau, 2019), if those figures were available. In addition to the applicable STEPS dimensions, we present the benefits and challenges of the sharing economy for each group as a *receiver of shared resources* via icons. A short feasibility analysis is also given to highlight if shared resources would be easy to implement, effective, and equitable for specific groups. We finish the table with recommendations derived from the focus group results and STEPS. Different vulnerable groups including carless; asset poor; racial and ethnic minorities; older adult; immigrants; LGBTQ+ individuals; and required workers have a higher feasibility for implementation. These groups tend to have higher access to technology to leverage shared resources and have a more varied range of income levels, which gives them advantages in a disaster. Several groups including those who are unbanked (or underbanked), individuals with disabilities, hospital bound, undocumented immigrants, and homeless were rated on the low end. While shared resources would greatly benefit these groups, a number of challenges exist related to locating these populations and ensuring they can engage with shared platforms. Indeed, all 18 identified vulnerable groups have at least one challenge for implementing shared resources, and ten groups have at least three major challenges.

Table 8: Vulnerable Groups Matrix – Definition and Background

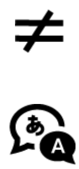
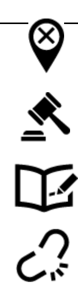
Vulnerable Group	Definition	Primary STEPS Dimensions	American Community Survey (% of California Residents)
Carless	Do not own a personal auto vehicle	Spatial Temporal Economic	7.7% do not own a vehicle
Low-Income	Under the poverty line based on household size; may also include individuals who do not earn a living wage	Economic	13.3% are below the poverty line
Unbanked and Underbanked	Do not have a bank account and/or a credit or debit card	Economic	Not available
Asset Poor	Have less than $500 in cash assets available for use	Economic	Not available
Racial and Ethnic Minority	Are not in a dominant position and suffer discrimination based on physical and/or cultural traits	Spatial Economic Social	27.9% Non-White-alone); 39.3% Hispanic or Latino
Older Adults	Age 65 and over	Temporal Economic Physiological Social	13.2% age 65 and over
Physically Disabled	Physical impairment that substantially limits major life activity	Temporal Economic Physiological Social	10.2% with some type of disability
Cognitively Disabled	Learning or intellectual impairment that substantially limits development and/or major life activity	Economic Physiological Social	4.2% with some type of disability
Psychologically Disabled	Psychological impairment that substantially limits major life activity; includes mental conditions	Economic Physiological Social	10.7% with some type of disability
Homebound	Unable to leave home; individuals may also be socially isolated	Spatial Physiological Social	5.5% age 18+ with "independent living difficulties"
Assisted Living	Located at a nursing home or other similar types of facilities	Spatial Physiological Economic Social	Not available
Hospital Bound	Located at a hospital due to health reasons; may be permanent or temporary	Spatial Temporal Physiological	Not available

		Economic Social	
Immigrant	From a different country and comes to live permanently; may or may not be a citizen	Spatial Economic Social	27.3% are foreign-born
Undocumented Immigrant	From a different country and do not have legal immigration status	Spatial Economic Social	Not available
Non-Native English Speakers	Speak a language other than English (i.e., English as a second language)	Spatial Economic Social	44.6% (Age 5+) do not speak English at home; 6.8% households are limited English-speaking
LGBTQ+ (Lesbian-gay-bisexual-transgender-queer-other self-identification)	Gender-based and sexuality-based identity	Social	Not available
Homeless	Without an established or regular home	Spatial Temporal Physiological Economic Social	Not available
Required Workers	Must work, by law, in disaster events	Spatial Temporal	Not available

Table 9: Vulnerable Groups Matrix – Shared Mobility Opportunity and Challenges

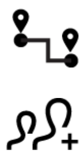
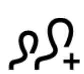
Vulnerable Group	**Vulnerable Group as a Recipient of Shared Resources**			
	Shared Resource Opportunities	**Shared Resource Challenges**	**Analysis and Feasibility**	**Recommendations based on Focus Groups and STEPS Framework**
Carless			Carless populations range from those without resources to own a vehicle to those in dense environments who choose to forgo car ownership. There is a wide range of opportunities, and this group has higher technology usage than other groups. However, challenges exist locating the population and not having enough capacity to evacuate enough people.	Develop multi-modal system that prioritizes public transit with private companies fulfilling first-mile, last-mile Disseminate resource information ahead of time to encourage compliance Create system with meeting points for different resources (e.g., rides to shelters, medical attention)

Low-Income			Low-income individuals often choose to not evacuate due to the high costs. Shared sheltering is the clearest benefit for reducing costs and increasing the number of resources available should aid in both evacuating and sheltering. However, low-income individuals typically have less access to technology and may be subjected to price gouging.	Develop multi-modal system that prioritizes public transit with private companies fulfilling first-mile, last-mile Ensure that prices are kept low (no surge) or provide resources for free to evacuees Disseminate information about resources (e.g., assistance filing insurance claims, free air masks) during reentry phase
Unbanked and Underbanked			Similar to low-income, unbanked individuals could benefit substantially from reduced costs of sheltering and transportation. However, without access to a bank or credit card, they will most likely be unable to pay if the service is not free. They also have lower rates of technology usage.	Ensure that prices are kept low (no surge) or provide resources for free to evacuees Allow evacuees to pay for resources (if needed) through multiple payment methods, including cash Provide information on evacuation and reentry resources or assistance organizations (e.g., Red Cross) beforehand
Asset Poor			Asset poor usually have credit cards, which allows them to engage with the sharing economy. With the low cost of transportation and sheltering through shared resources, they may be more likely to evacuate despite the lack of cash. However, they may still not have access to technology and may be subjected to price gouging.	Ensure that prices are kept low (no surge) or provide resources for free to evacuees Allow evacuees to pay for resources (if needed) through multiple payment methods, including credit cards

Racial and Ethnic Minority			Racial and ethnic minorities are a diverse group of people with a wide range of incomes, education levels, and access to technology. In this case, shared resources via neighbors and sharing economy companies would work well. However, shared resources provided by strangers might be ineffective as these minorities may experience further discrimination as they attempt to request transportation or sheltering.	Increase trust by increasing the vetting process for drivers and hosts Develop neighborhood-based programs that leverage similarities in cultural and social dimensions Train drivers and hosts to provide service to all evacuees, regardless of race or ethnicity Disseminate information in a variety of forms to communities so they gain a better understanding of real threats of the hazard
Older Adults			Given the rising population of older adults, evacuation needs for this group will continue to grow. Older adults would gain the most through point-to-point service and opportunities to maintain social connections. The extra resources may also encourage elderly individuals to evacuate. However, a digital divide exists, and there may be liability concerns related to medical needs. Extra training for providers may also be needed to help older adults move.	Partner with local governments to increase security and safety Ensure that costs remain low Train drivers and hosts to assist older adults in evacuations Ensure information is disseminated across multiple media platforms Ensure that shelters and other housing facilities have necessary medical equipment (e.g., oxygen tanks, access to dialysis centers)
Physically Disabled			Individuals with physical disabilities are often not provided the necessary services or care that is required through civil rights protections. Increased resources, point-to-point service, and increased compliance are all benefits. However, helping these individuals does lead to liability	Create partnerships with paratransit that could identify and assist individuals with disabilities Include an option in digital applications to denote disability or assistive device or animal ownership

			concerns and would require provider training. Accessible vehicles may also not be available.	Train drivers and hosts to assist physically disabled individuals in evacuation situations
Cognitively Disabled			Individuals with cognitive disabilities are harder to identify and locate than other disabled individuals. Many often have a caregiver who takes care of them more regularly. Given the difficulties and the lower level of self-sufficiency, cogitatively disabled individuals may not benefit substantially.	Create partnerships with paratransit that could identify and assist individuals with disabilities Include an option in the application to denote disability or assistive device or service animal ownership Train drivers and hosts to assist cognitively disabled individuals
Psychologically Disabled			Similar to individuals with cognitive disabilities, individuals with psychological disabilities are harder to identify and locate. This group does include a higher proportion of those who are self-sufficient and engaged with technology. Individuals with psychological disabilities may benefit from social connections through shared resources, especially housing.	Create partnerships with paratransit that could identify and assist individuals with disabilities Include an option in digital applications to denote disability or assistive device or service animal ownership Train drivers and hosts to assist psychologically disabled individuals in evacuation situations

Homebound			Homebound individuals are difficult to identify and locate and they may have additional characteristics (such as having a physical disability). Communicating with these individuals may also pose a challenge. However, these individuals would greatly benefit from point-to-point transportation and the increase of social connections in a disaster.	Create partnerships with paratransit and leverage neighborhood networks that could identify and assist homebound individuals Ensure resource information is disseminated across multiple media platforms
Assisted Living			Assisted living centers may require high-capacity shuttles to effectively evacuate their facilities. Resources through companies may be a more immediate possibility. These centers have also struggled in recent disasters in evacuating residents so any type of shared resources may be effective.	Create partnerships with paratransit and assisted care facilities that could assist evacuees in transportation and find proper shelter with adequate support Prepare go bags for residents with necessary medicine and/or medical information in case of evacuation
Hospital Bound			Hospitals may require high-capacity shuttles to be able to effectively evacuate their facilities. However, hospitals face additional challenges related to the continuous care of their patients, which the sharing economy would not be able to provide in the form of vehicles or sheltering.	Create partnerships with paratransit and hospitals that could assist evacuees in transportation and find proper shelter with adequate support Prepare go bags for patients with necessary medicine and/or medical information in case of evacuation
Immigrant			Immigrants are a diverse group of people with relatively high access to technology. Many immigrants are also well established in their community where they may be able to leverage their resources. Shared resources in the neighborhood is the most	Provide information on available resources multiple languages Include credentialing information for hosts to increase trust Develop neighbor-to-neighbor networks to

			straight-forward use case, especially since communication, language, and cultural barriers might exist.	maximize trust and resource sharing
Undocumented Immigrant			Locating undocumented immigrants is very challenging and encouraging them to accept assistance in situations where they may be tracked is difficult. Undocumented immigrants are likely more willing to congregate with friends and family, which would increase social connections.	Provide information on available resources multiple languages Develop neighbor-to-neighbor networks to maximize trust Provide information on resources that are not government sponsored to ease fears of document checks
Non-Native English Speakers			Non-native English speakers often have difficulty navigating relief programs, which are predominately in English. Pairing and matching by language or using automated translations could be effective in offering services. However, cultural and communication barriers along with discrimination may be a problem.	Provide information on available resources multiple languages Develop neighbor-to-neighbor networks to maximize trust and resource sharing
LGBTQ+		≠	LGBTQ+ individuals are economically diverse and generally have high access to technology. However, some individuals may experience continued discrimination with shared transportation or sheltering. Adequate matching would help maintain social connections.	Train drivers and hosts to provide service to all evacuees, regardless of sexuality or gender Develop a peer-to-peer network that leverages community similarities

Homeless			Increasing the number of resources to raise compliance of orders and decrease costs are the most positive benefits. However, homeless individuals are challenging to locate and much of the public is unlikely to want to engage with the homeless, since they are often equated with psychological issues.	Ensure that prices are kept low (no surge) or provide resources for free to evacuees Leverage pre-existing homeless shelter expertise in finding adequate housing and transportation
Required Workers			While not typically viewed as a vulnerable group, required workers may benefit in disasters with designated housing near the disaster area. These individuals have access to technology, but they may be safer in a location away from the disaster.	Encourage community members to provide resources to disaster workers

Legend of Sharing Opportunities

- Increase housing or sheltering resources
- Increase evacuation compliance
- Increase transportation accessibility
- Decrease the cost of transportation or sheltering
- Maintain social connections and decrease psychological impacts

Legend of Sharing Challenges

- Not enough resources available and/or difficulty finding these resources
- Hard to locate individuals
- A digital divide (i.e., low access to technology)
- Increase costs or potential for price gouging
- High liability for the provider of service
- Likelihood for discrimination
- Cultural differences
- Communication challenges stemming from a lack of understanding or an inability to explain services
- Additional training may be required to provide service
- Evacuating may not be the best decision, and sheltering-in-place may be safer

5.7) Conclusion and Recommendations

This research suggests that clear resource deficiencies remain in evacuating citizens, including those most vulnerable. While the sharing economy could offer more equitable outcomes for disaster response and relief, the STEPS equity framework and focus groups with four vulnerable groups – older adult, individuals with disabilities, low-income, and Spanish-speaking – indicate that a substantial number of limitations remain. Indeed, we found that of the 18 identified vulnerable groups, all face at least one critical challenge in implementing shared resources with 10 groups experiencing three or more barriers to implementation. While some of the barriers could be overcome quickly such as developing partnerships to decrease the potential for price gouging, other challenges such as high liability, the digital divide, and locating vulnerable groups would take considerably more effort and planning on the part of agencies and practitioners.

While numerous challenges remain in developing a comprehensive shared resource strategy, public agencies can still begin to build a more structured framework. Based on the focus group results and a consolidation of recommendations from the STEPS framework (Table 8 and 9), we recommend that agencies should consider adding shared resources into strategies for evacuation and sheltering response as seen in Table 10. These recommendations serve as a starting point for building practical strategies and encouraging more research on social equity in this alternative evacuation strategy.

We also note that multiple public agencies and community organizations will need to develop partnerships (or at least working relationships) with sharing economy companies. Several additional items need to be considered in the planning process. First, local areas need to determine if resources from sharing economy companies are even available. These companies often do not operate in rural areas of California (or rural areas in the U.S.). Consequently, a community-based strategy that leverages neighbors and private citizens will be most effective (e.g., carpooling networks, homesharing networks, phone trees, and Community Emergency Response Team (CERT) integration). We note that these community-based strategies should not be restricted to rural areas but are also crucial for disaster preparedness in larger cities and suburban communities. Second, several entities need to be consulted in developing a shared resource strategy. Specifically, law enforcement agencies, such as the state highway patrol, are often responsible for on-the-ground evacuation response and can restrict access to areas where sharing economy vehicles may attempt to go. Finally, the relationships need to be developed with the various agencies (e.g., transportation, public transit, emergency management, firefighting, law enforcement, CBOs, etc.), which may differ by jurisdiction and even by hazard. Flexibility within these relationships is crucial, which is why we recommend beginning with situational awareness and working relationships before developing more structured shared resource partnerships.

Table 10: Recommendations for Public Agencies using the Focus Group Results STEPS Framework

Literature	Recommendation	Potential Equitable Outcomes	S	T	E	P	S
Vulnerable populations, in particular, may face a severe shortage of resources when trying to	Building more robust public transit-based evacuation plans that	• Provides additional resources for carless,	X	X	X	X	

evacuate, especially carless and special needs households (Renne et al., 2008). Shared modes (e.g., TNCs) may be used to complete first- and last-mile gaps in the transportation network (Meyer and Shaheen, 2017).	leverage the sharing economy for first-mile, last-mile connections and post-disaster transportation	low-income, and transit-reliant individuals • Promotes a faster evacuation (in trip time), especially for those physically unable to evacuate quickly • Assists in decreasing evacuation congestion, thus improving evacuation times					
Significant planning is needed to ensure that evacuees have transportation to shelters and access to free resources, particularly vulnerable populations (Litman, 2006; Cahalan and Renne, 2007; Renne et al., 2008). Predetermined pick up points provide easy-to-find locations for evacuating households who need transportation (The City of New Orleans, 2018).	Creating a TNC and/or public transit plan with meeting points for different resources	• Increases the number of rides to shelters • Offers locations for medical attention and free basic necessities (e.g., water, N-95 masks)	X	X	X	X	X
Individuals with disabilities have a variety of different physical and mental conditions, including those that are not readily visible, that inhibit their ability to evacuate (Renne et al., 2008), are less likely to have an evacuation plan (Spence et al., 2007), and are more likely to evacuate later than recommended for hurricanes (Ng et al., 2015). Public transit agencies with their own accessible vehicles or contracts with paratransit operators have some capacity to meet mobility and evacuation needs (SMART Train, 2017; Napa Valley Register, 2017; The City of New Orleans, 2018), but advanced planning is necessary to assist public transit-dependent evacuees (Bish, 2011).	Creating partnerships with paratransit providers to identity and assist individuals with disabilities	• Increases availability of accessible vehicles to allow for spatially broader and faster coverage in an evacuation • Ensures that individuals with disabilities trust drivers and resource providers • Ensures that resources providers are properly trained to assist individuals with disabilities	X	X		X	X
Shared mobility modes may be inaccessible to certain populations due to financial barriers (Shaheen et al., 2016). Services that allow for fare payment in a variety of ways (e.g., cash, through smartphone apps) can increase mobility and accessibility for different demographic groups,	Developing regulations that keep costs of resources low to avoid surging and allowing evacuees to pay for resources (if absolutely necessary) through multiple payment methods including cash	• Improves the ability of low-income, unbanked, and asset poor individuals to use services • Increases evacuee trust of companies			X		X

especially those with limited resources (Shaheen et al., 2017).							
Evacuees have gone without adequate food, water, prescriptions, and medical care at shelters (Brodie et al., 2006), and individuals with significant medical conditions often do not have guaranteed medical attention at evacuation destinations (Renne et al., 2008). While some shelters during the California wildfires faced considerable difficulties in maintaining quality of life due to capacity challenges and spread of illness, others were able to act as distribution centers for resources and aid during and after the fires (Wong et al., 2020).	Ensuring that shared shelters and other accommodations have necessary medical equipment (e.g., oxygen tanks, access to dialysis centers) for fire-based health challenges (e.g., smoke inhalation) in addition to medical supplies to treat chronic illnesses (e.g., insulin for people with diabetes)	• Improve health outcomes of older adults, medically fragile populations, and individuals with disabilities			X	X	
Persistent challenges remain in locating and communicating with vulnerable populations, especially those without mobility (Turner et al., 2010). Voluntary and adequately confidential registries (among other tools) can be used by emergency planners to identify vulnerable populations and more easily assist individuals with resources, such as transportation (Hoffman, 2008).	Developing a system within TNC/homesharing applications or a public registry that denotes vulnerable individuals that need extra physical assistance, have a disability, and/or own a pet/service animal	• Increases knowledge of vulnerable individuals' locations and assistance needs • Improves reaction time of resource providers to reach vulnerable populations	X	X	X	X	X
Neighbors are a common source of receiving information during wildfires (Wong et al., 2020), especially given that communication may be unavailable (Wong et al., 2020). Indeed, only 56% and 71% of households with incomes under $30,000 have access to broadband Internet and smartphones, respectively (Pew Research, 2019a,b). Social cohesion, in particular characteristics such as sense of community and collective problem solving, increases preparedness and reduces vulnerabilities in wildfires (Prior and Eriksen, 2013), while social networks influence evacuation choice in hurricanes (Sadri et al., 2017).	Working with neighborhood associations to develop localized community-based plans to ensure transportation for neighbors	• Offers a more trustworthy (and maybe more effective) strategy for all vulnerable groups • Provides more evacuation options and resources for neighbors					X

Non-English speakers and ethnic minorities face challenges in receiving and understanding warning messages (Perry, 1987); sometimes receive warnings in other languages later than English warnings in wildfires (Shyong, 2019); and face language and cultural barriers in accessing post-disaster funding and shelter (Cutter et al., 2003). Disseminating information in a variety of forms and languages can spread awareness and understanding of evacuation orders (Perry, 1987), and lessons can be learned from multi-language outreach by public transit agencies (Turner et al., 2010).	Providing resource information (and evacuation orders) in multiple languages and through multiple channels	• Ensures information is understood by non-English speakers • Improves the speed of information dissemination in non-English speaking communities and ethnic enclaves • Improves trust between non-English speaking communities and public agencies		X			X
Lack of trust can be a barrier to exchanging goods and services via the sharing economy under normal conditions (Mohlmann, 2015; Hamari et al., 2016). Risk perceptions have been found to influence wildfire evacuation behavior (McCaffrey et al., 2018; Toledo et al., 2018; Lovreglio et al., 2019), higher trust levels (as opposed to lower levels) prior to a disaster lead to a larger trust-increasing effect after the disaster (Dussaillant and Guzman, 2014), and setting credentials for shared mobility can increase trust (Taylor, 2019).	Increasing credentialing of drivers and host for both companies and private providers	• Increases evacuee trust of shared resources companies and providers					X
Most large U.S. cities do not have adequate plans to assist and evacuate carless and vulnerable populations (Renne and Mayorga, 2018) and many vulnerable populations are unable to evacuate on their own (Renne et al., 2008). Social cohesion increases psycho-social and material support to community members, which helps increase protective action in a wildfire (Prior and Eriksen, 2013).	Offering training through Community Emergency Response Teams (CERTs) or other organization in how to properly assist others in evacuations	• Ensures that providers safely assist vulnerable populations • Reduces potential liability on providers and companies • Decreases likelihood of discrimination against vulnerable populations • Improves safety of providers and individuals' willingness to assist in evacuations			X		X
A significant gap exists between perceived disaster preparedness and actually taking steps to prepare (e.g., owning items for emergencies	Requiring assisted-care centers and hospitals to prepare go bags for patients	• Smooths and speeds up the evacuation process (especially for a TNC-based evacuation)		X		X	

such as canned goods, flashlights, and "go bags") (Ablah et al., 2009). Furthermore, hospitals and other healthcare facilities have faced significant challenges in successfully evacuating patients (Fink, 2013). "Go bags" for emergencies can better prepare individuals, particularly those who face additional risks, such as medical conditions (Gusmano and Rodwin, 2010), and hospitals and healthcare facilities have successfully evacuated from wildfires (Espinoza and Kovney, 2017).	with necessary medicine and medical information	• Improves continuity of care for patients and health outcomes					
Cultural and language barriers along with communication method can negatively impact the rapid dissemination of information to vulnerable populations (Turner et al., 2010). Agencies have struggled to communicate evacuation orders and resources effectively during wildfires due to the speed that fires travel (Wong et al., 2020). Communicating information, such as resource availability, using public education methods and best practices from public transit agencies can help to overcome some (but not all) communication barriers with vulnerable populations (Turner et al., 2010).	Disseminating information about resources (e.g., assistance filing insurance claims, TNC or public transit rides, free air masks) prior to evacuations and during the reentry phase through both government agencies and CBOs	• Improves long-term economic and health outcomes for impacted evacuees, especially high-risk populations • Offers a pathway for undocumented immigrants to gain needed resources without fear of document checks • Improves reentry process and subsequent access to resources			X	X	X
Different disasters, with varying geographical scales and warnings, have major transportation issues including: evacuating people, supplying emergency services (including personnel to assist), and transporting search and rescue teams (Litman, 2006). Companies have worked to create mechanisms for helping disaster workers, such as actions by Airbnb to sign memoranda of understanding with cities and create a disaster response programs to house both evacuees and disaster workers (Chapter 3). Local citizens provide much needed surge capacity and assistance through informal	Encouraging community members to offer transportation and sheltering assistance to required and disaster workers	• Allows workers to remain close to the disaster to improve response • Improves trust and relationships between community members and disasters workers	X	X			X

volunteerism (Whittaker et al., 2015).							
Vulnerable populations face considerable needs, barriers, and challenges in receiving communications and evacuating during disasters (Cahalan and Renne, 2007; Renne et al., 2008; Turner et al., 2010). Strengthening participatory planning approaches that analyze risks and vulnerabilities (among other strategies) can reduce disaster impacts on communities and increase resilience (UNDRR, 2011).	Including all vulnerable groups in the planning process for emergency evacuations	• Increases the input of vulnerable groups in evacuation plans and increases equitable outcomes for those groups • Provides resources that may be useful for a variety of vulnerable groups	X	X	X	X	X

In addition, we offer several key research directions for continued work in this sub-field of evacuations. These research recommendations are not meant to encompass the entire field of evacuations but serve as a primer for future work that could build off of this research.

- Measure the number of current sharing economy assets and the availability of assets during emergency conditions;
- Determine the risk perception of individual providers and users in the sharing economy in cases of disasters;
- Study the capacity of other sharing economy assets that could increase social equity and improve outcomes such as:
  - Bikesharing – on-demand access to bicycles at a variety of pick-up and drop-off locations for one-way or roundtrip travel;
  - Carpooling – grouping of travelers into a private automobile for trips between home and work locations or for trips that would have otherwise occurred;
  - Carsharing – short-term access to automobiles, allowing users to gain the benefits of a private automobile while forgoing auto ownership costs;
  - Scooter Sharing – on-demand access to electric scooters at a variety of pick-up and drop-off locations for one-way or roundtrip travel;
- Focus additional research on the sharing economy to cover small-scale evacuations, non-hurricane evacuations, and rural evacuations; and
- Consider the role of innovative mobility beyond the sharing economy, including electric vehicles, automated vehicles, and urban air mobility (e.g., automated and electric helicopters), and how these new modes could improve (or harm) social equity outcomes.

Finally, we note that a clear next step for this research would be to conduct an extensive survey of vulnerable individuals who were impacted by the California wildfires and additional focus groups for the same groups and other vulnerable groups. This would likely require a combination of survey methods to reach all individuals, particularly those who were displaced. Future surveys should also take cues from recent work on social capital and social networks in evacuations (Sadri et al., 2017; Sadri et al., 2018). Indeed, the feasibility of the sharing economy strategy likely rests on the strength of social capital in the community, as we found in the requirements of trust in the focus groups. Moreover, we note that the sharing economy will require strong communication mechanisms including a mixture of high-tech strategies (e.g., social media) and low-tech strategies (e.g., face-to-face interactions). Research has found that social networks can impact joint decision-making for regular travel (Sadri et al., 2015) and large-event travel (Rezende et al., 2016). Other research on disasters and large events also have found the presence of the "power law," where fewer nodes can be highly influential in disseminating information (Sadri et al., 2019). This indicates that any future sharing economy model could make use of several key people in the community to increase resources. Social media can also be used to determine resource needs (Ukkusuri et al., 2014) and be extended to the present topic of the sharing economy as a primary mechanism for matching. Finally, other sharing economy research, such as Borowski and Stathopoulos (2020), should continue to address TNCs for evacuations from a much-needed demand perspective using mode choice modeling. With this growing interest in shared resource mechanisms, a multi-method approach that leverages both stated preference and revealed preference surveys from both non-evacuees and evacuees will be critical in determining how capacity and demand for shared resources can improve equitable outcomes.

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Chapter 6: Understanding the Willingness to Share Resources in a Hurricane Evacuation: A Multi-Modeling Approach

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ABSTRACT

Recent improvements in technology and communication have allowed for the proliferation of the sharing economy, coinciding with the growing need for transportation and sheltering resources in disasters. The sharing economy (e.g., Airbnb, Lyft, and Uber) through willing private citizens may supplement public resources. To understand influencers on the willingness to share resources in evacuations, we employed a multi-modeling approach across four sharing scenarios using three model types: 1) four binary logit models that capture each scenario separately; 2) a multi-choice latent class choice model (LCCM) that jointly estimates multiple scenarios via a latent class structure; and 3) a portfolio choice model (PCM) that estimates dimensional dependency of the four scenarios. We test our approach by employing evacuee data (n=368) from an online survey of individuals impacted by Hurricane Irma in 2017.

The multi-model approach uncovered behavioral nuances (and similarities) that would be obscured if only a single model type was used. First, the multi-choice LCCM and PCM models uncovered correlation between the scenarios that could not be found via the binary logit models. In particular, willingness to share for both transportation scenarios and both sheltering scenarios was correlated. Second, the multi-choice LCCM found three clear classes – transportation sharers, adverse sharers, and interested sharers – but weak demographic characteristics. Transportation sharers were more likely to be female, lower-income, and residents of Southwest Florida compared to adverse sharers. Interested sharers were more likely to be male, long-time residents, and higher-income compared to adverse sharers. Third, families with children were unwilling to share regardless of the model, while spare capacity (i.e., seatbelts, spare beds) had a positive but somewhat insignificant influence on sharing across models. Fifth, experienced home sharers were more willing to share shelter in the binary logit and PCM models. Finally, many demographic variables (i.e., age, homeownership, race, household size, residence type) across all three model types were largely insignificant, indicating that other behavioral motivators are likely influencing willingness to share in an evacuation. We suggest that local agencies consider more holistic mechanisms for sharing that incorporate multiple resource types across time (i.e., before, during, and after a hurricane evacuation).

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

6.1) Introduction

In recent years, travel behavior analysis through discrete choice modeling has begun to expand traditional model structures to better assess behavior including contexts with multiple co-dependent choices. This direction in the field has grown out of the improved understanding that choices are often correlated and interdependent. 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 a nested logit model makes no temporal assumption (Bian, 2017). Consequently, different model types with varying benefits and limitations are needed to more fully and comprehensively assess behavior in contexts with multiple choices.

In the last two decades, the rise of 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 a number of disasters in the United States (US). Since Hurricane Sandy in 2012, sharing economy companies – such as Uber, Lyft, and Airbnb – have been increasing their actions in disaster response and relief (Wong et al., 2018a). Research has also found that private citizens could augment existing resources by offering transportation and sheltering to other evacuees. Indeed, recent work has found that individuals are moderately willing to offer sheltering to other citizens and strongly willing to offer transportation in both wildfires and hurricanes (Wong and Shaheen, 2019; Chapter 3). Other studies have found that there is also a likely demand for shared vehicles via ridesharing or transportation network companies (TNCs) in disasters in urban areas (Li et al., 2018; Borowski and Stathopoulos, 2020). However, little is known about the factors that impact an individual's willingness to provide resources in a disaster. Moreover, different types of resources can be provided at different points of time before, during, and after an evacuation. This sets up a context where there are multiple sharing choices (denoted as sharing scenarios throughout this paper). Given the potential of the sharing economy and a multi-scenario context, we developed two research questions to guide our study:

1. What factors influence the willingness to share resources – either transportation 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?

Using data collected from individuals impacted by Hurricane Irma in 2017, this paper explores the willingness of private citizens to offer their shared resources across four sharing scenarios (two for transportation and two for sheltering) in evacuations. We use a subset of evacuees (n=368) from the online survey of individuals impacted by Hurricane Irma in 2017 (n=645), which we collected from October to December 2017. We assess the factors that impact willingness to share by employing three models forms to determine behavioral similarities and differences. First, we develop four 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. Second, we develop a multi-choice latent class choice model (LCCM) that allows for the estimation of multiple scenarios that are connected via a latent class choice model (LCCM) structure. This expansion of the traditional LCCM also allows the estimation of a class membership model, which segments the population into different classes (e.g., sharers, non-sharers) through demographic characteristics and perceptions. Finally, we develop a portfolio choice model (PCM) that captures dependency among sharing scenarios without resorting to a hierarchical or sequential framework. These three modeling forms together form a comprehensive behavioral story about the factors that impact willingness to share resources in an evacuation.

This paper is structured as follows. First, we briefly present the literature associated with the sharing economy evacuation resource strategy, joint modeling, and latent class choice models. An in-depth review of more traditional utility maximizing models (e.g., binary and multinomial logits) can be found in Ben-Akiva and Lerman (1985) and Train (2009). Next, we present the methods employed for: 1) a multi-choice (LCCM), which links different choices via a latent class structure and 2) a portfolio choice model (PCM), which captures dimensional dependency. Next, we present our findings from the binary logit models, LCCM, and PCM on willingness to share and offer a modeling discussion on behavioral similarities and differences between model types. Finally, we offer several recommendations on developing a sharing economy framework in hurricane evacuations based on our results.

6.2) Literature Review

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

6.2.1) 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 that are needed for 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 peer-to-peer sharing economy service (e.g., Airbnb), indicating the growth of this mechanism for finding 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 disadvantaged 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 a lack of resources is 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 concerns (Litman, 2006), considerably more resources are needed to ensure that all people, especially those most disadvantaged are able to evacuate safely. These 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; Rodriguez et al., 2007; Renne et al., 2008; Sanchez and Brenman, 2008; Renne et al. 2009; 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 (Chapter 3). The growth of these companies has coincided in 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 (Chapter 3). Yet, experts were concerned that the sharing economy might not ensure that providers of resources are reliable, safe, and trained for disaster situations; not reduce road and communication network congestion; fail to overcome the digital divide (i.e., inequality in accessing computers/Internet); and lack low costs or equitable outcomes (Chapter 3).

With this assessment of key benefits and limitations, research has also focused on a peer-to-peer model. Li et al. (2018) determined that ride-hailing could be a viable evacuation strategy for China and that carless evacuees would opt to take these transportation options, indicating clear demand. Chapter 3 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 that a significant number of evacuating vehicles had spare capacity (88.9% of evacuees with one or more spare seatbelts). Recent work has also found that for no-notice evacuations, there is substantial demand for transportation via ridesourcing in urban evacuations and that demographic factors (e.g., race, income, gender) and disaster-factors (i.e., severity, evacuation distance, immediacy) impacted demand (Borowski, 2020). Other work on social networks 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 (Chapter 3; Wong and Shaheen, 2019).

6.2.2) 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), transportation mode and 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 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 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 methodology in Paleti et al. (2013) by estimating random parameters that captured interdependencies in the utility equations for each choice. Finally, Guo et al. (2020) jointly modeled long-term residence choice, job choice decision, and short-term commute mode choices using panel data collected from Shenyang, China. The resulting model, a multi-dimensional mixed logit model, found significant dependencies among choice.

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 found strong joint preference between duration of vacation and transportation mode. The PCM has also been used to assess potential correlation among evacuation choices (Chapter 7). The results of the work found a joint preference for early departure-nighttime evacuations and early departure-highway evacuations. Two key benefits of the PCM model are that it can be estimated as a multinomial logit and it does 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. 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. We provide additional background on LCCMs below to highlight their uses.

6.2.3) 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 people 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. 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, holding homogeneous preferences (i.e., identical coefficients for attributes of the decision-maker). Many studies using different datasets have shown that the LCCM is capable of representing 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; Chapter 7; Chapter 8). Most LCCM and non-LCCM studies have concentrated on one dimension of behavior. For example, in the disaster choice making context, the single dimension choice of whether to evacuate or not evacuate has been assessed via traditional binary logit models (Whitehead et al., 2000; Zhang et al., 2004; Smith and McCarty, 2009; Stein et al., 2010; Hasan et al., 2011; Huang et al., 2012; Murray-Tuite et al., 2012; Murray-Tuite and Wolshon, 2013; Wong et al., 2018b), mixed logit models (Deka and Carnegie, 2010; Solis et al., 2010; Hasan et al., 2011; Xu et al., 2016; Yin et al., 2016), and LCCM models (Urata and Pel, 2018; McCaffrey et al., 2018; Chapter 7). However, in many choice contexts including evacuations, choices are inherently correlated and interdependent. For example, mode choice and destination in evacuations have been found to impact each other (Bian, 2017; Chapter 7), suggesting the need to model these choices concurrently (i.e., jointly). We also recognize that other choice contexts, including multiple stated preference scenarios, can also be modeled jointly. Specifically, a joint analysis would enable the assessment of characteristics of the decision-maker that impact all scenarios. In our context of a shared resource strategy, we consider these 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. In this paper, we employ an extension of the traditional LCCM to handle multiple scenarios to identify individuals' potential segments and heterogeneous preferences for offering transportation and sheltering resources in an evacuation.

6.3) Methodology

We present the methodology for this paper by framing it in the context of the Hurricane Irma survey and four sharing scenarios we developed to assess willingness to share resources in a hurricane evacuation. Using this framing for improved understanding, we provide equations for the multi-choice LCCM. We also provide a derivation of the (Expectation-Maximization) EM algorithm used to estimate the model in Appendix A. We also briefly discuss the portfolio choice model (PCM) methodology, which is used as a comparison to the multi-choice LCCM.

6.3.1) Hurricane Irma Survey Data

Hurricane Irma 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 (National Oceanic and Atmospheric Administration, 2018; Maul, 2018). The storm caused approximately $50 billion in damages and led to 92 deaths in the U.S. (National Oceanic and Atmospheric Administration, 2018). From October to December 2017, we distributed an online survey to individuals impacted by Hurricane Irma in September 2017 across the state of Florida.

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 the population size of their jurisdiction and their proximity to the disaster. 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.

In Table A1 of the Appendix, Hurricane Irma survey respondents were mostly from Brevard (53.2%), Lee (17.2%) and Collier (13.3%) counties in Florida. All these counties had substantial populations that evacuated, while the latter two were directly impacted by Irma. Respondents were generally higher-income (30.1% above $100,000 for the household) and well educated (just 6.5% with a high school degree or less). The sample also skewed whiter (94.0%) and female (81.9%). 94.3% drive to work/school alone. Much of this skew away from the general population is a function of the 1) targeted locations of the survey along heavily impacted but wealthier coastlines, and 2) the online survey instrument. Yet, other characteristics such as age, employment status, household size and type, length of residence, and hazard experience were more varied. In addition, 97.4% of respondents stated that they were the sole, primary, or equal decision-maker in the household. We found that 69.5% complied with mandatory evacuation orders while 30.5% did not. This result may be a conservative estimate of compliance as a telephone poll of Florida voters found a 43% non-compliance rate (Mason-Dixon Polling and Research, 2017). Of those who reported they did not receive a mandatory evacuation order, 46.4% evacuated (shadow evacuation) and 53.6% did not evacuate. Additional descriptions of the Hurricane Irma respondents can be found in Table A1 in the Appendix and in Wong et al. (2018b).

The Hurricane Irma dataset has several key limitations that limits some of our conclusions. First, the online survey exhibits self-selection bias as individuals opt into the study. Individuals with greater concern of evacuation planning may be more likely to fill out the survey. We attempted to address this by providing a lottery incentive and asking over 20 agencies with different functions (e.g., transportation, emergency management) to distribute the survey. Several news sources also distributed the survey, which increased coverage across a wider population. We also acknowledge online surveys have some sampling bias as the online surveys only reach individuals with Internet access. This limits the scope of the study population, while also oversampling younger (Kaplowitz et al., 2004) and wealthier populations (Sheehan and Hoy, 1999). We also found that for our survey, a high number of respondents were concentrated in three counties – Brevard, Lee and Collier – for Hurricane Irma. The sample geographies were wealthier, more highly educated, and racially whiter than the impacted area and Florida. This skew in results is a partially a function of our targeted strategy of finding impacted coastal communities. Consequently, we are unable to determine if those not represented in the survey (e.g., vulnerable populations) are willing to share resources. However, we note that most vulnerable populations would likely be users of shared resources, not providers. Future research could reduce the data bias by employing multiple survey methods or finding a randomized sample of individuals impacted by a disaster.

6.3.2) Hurricane Irma Sharing Scenarios

We developed four sharing scenarios where individuals were asked their willingness to provide resources to a non-household member in a future disaster event. Table 1 provides a description of the four scenarios:

- Share transportation before evacuating (S1-Transport-Before)
- Share transportation while evacuating (S2-Transport-During)
- Share shelter at a cost (S3-Shelter-Cost)
- Share shelter for free (S-Shelter-Free)

Respondents were asked their willingness to share their own private resources on a Likert scale from extremely unlikely (1) to extremely likely (5). While we captured this range of willingness, we wanted to more clearly assess *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 is intended to clearly define a group of individuals who would actually share in a disaster. Moreover, it allows for a simpler model structure when estimating our models by reducing the number of available alternatives.

Table 1: 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)			

We note that the characteristics of the individual(s) in need of resources was not specified. Shared resources could be used to help close social connections (e.g., friends, extended family), moderate social connections (e.g., neighbors, co-workers), or weak/no social connections (e.g., strangers). This limitation in the scenario design could be improved in future survey designs where the user of the shared resource is labeled. The user groups may also lead to differing responses on the willingness to deviate from the evacuation route or the maximum distance a provider would carry a passenger. Future surveys could also include a scenario to share transportation after the evacuation during the recovery period. Since we only asked evacuees about their willingness to offer transportation resources, our joint models have only a sample size of 368. We note additional limitations of the scenario design throughout the following model result section. Table 2 presents the descriptive statistics for the different scenarios. Additional descriptive statistics and further exploration of the sharing economy strategy can be found in Chapter 3 for Hurricane Irma and Wong and Shaheen (2019) for California Wildfires in 2017 and 2018.

Table 2: Likelihood to Share in a Future Disaster of Evacuees Only (n=368)

Likelihood	S1-Transport-Before	S2-Transport-During	S3-Shelter-Cost	S4-Shelter-Free
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%		

6.3.3 Portfolio Choice Model (PCM)

After constructing four binary logit models for each of the scenarios, we developed a portfolio choice model (PCM), which capture interdependency among choices via a bundling approach. Choices are combined to form a bundle of choices, which become the new alternatives in the choice set. PCMs have been widely used in tourism choice behavior as one’s transportation mode, destination, and length of trip are typically dependent (Dellaert et al., 1997; Grigolon et al., 2012; Van Cranenburgh et al., 2014a; Van Cranenburgh et al., 2014b). More recent work has used PCMs to model evacuation behavior, finding considerable joint preference and joint dislike among choice dimensions (Chapter 7). We use methodology provided in Van Cranenburgh et al. (2014a) to develop our PCM model. We combine the four scenarios (each composed of a binary decision) into bundles of choices to reach 16 possible portfolios (2*2*2*2). As is customary in the PCM literature, we assume i.i.d. EV Type I errors, which leads to closed form logit probabilities. Through a PCM structure, we are able to estimate the parameters of the different dimensions, possible interactions, and the impact of demographic characteristics on the dimensions. For the PCM, we retain all secondary interactions to provide a clear comparison of joint preferences. We also retain statistically significant demographic variables along with several slightly insignificant variables that are policy relevant and/or significant in the binary logit models (see Table A2 in the Appendix). We estimate the PCM as a multinomial logit model via the Python package Pylogit (Brathwaite and Walker, 2018). We note that we chose the PCM as the comparison model (as opposed to other joint models such as a nested logit) due to the lower sample size in our data, the simple behavioral understanding from a PCM, and the simple and flexible estimation of parameters for a PCM via a traditional multinomial logit model.

6.3.4) Methodology of the Multi-Choice Latent Class Choice Model (LCCM)

To better account for unobserved preferences and classes of individuals, we developed a multi-choice LCCM that connects scenarios (i.e., choices) via a membership structure. Following the methodology provided in El Zarwi et al. (2017), we first consider a class-specific model for the decision be extremely likely to share and all other responses, a binary choice. Our goal is to determine the probability an individual n makes a choice y to be extremely likely to share for alternative i (where $i = 1$ is extremely likely to share and $i = 0$ is not extremely likely to share). We chose this binary decision since *stated* extreme likelihood to share most reflects *revealed* willingness to share in a disaster. Note that this decision can be expanded to a multinomial decision by allowing for values beyond 0 and 1. The probability of making this decision is conditional on the characteristics of the decision-maker (Z_n), alternative specific characteristics (X_{ni}) and the decision-maker belonging to latent class s (where q_{ns} equals one and zero otherwise). This is 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 in the same manner as random utility maximization (RUM) models, we formulate 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 $V_{ni|s}$ is the systematic utility, x'_n is a vector of characteristics of the decision-maker and attributes of alternatives, β_s is a vector of estimable parameters specific to latent class s, and $\varepsilon_{ni|s}$ are disturbances associated to the utility. We assume that the disturbances are independent identically distributed (i.i.d.) Extreme Value errors across all individuals, alternatives, and latent classes. We now express the probability from equation (1) in terms of the utility from each latent class into the classical RUM function, where C is the choice set, as follows:

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

For the above formulation, we only consider a single choice (y_{ni}). We expand this formulation to consider the role of multiple choices. These multiple choices are connected via the latent classes. For this model, we consider the four sharing scenarios (Table 1) as separate choices that an individual could make. Each choice can be denoted as follows with choice context M:

For choice context 1 to M:

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

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

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

$$U_{ns} = V_{ns} + \varepsilon_{ns} = z_n' \tau_s + \varepsilon_{ns} \tag{6}$$

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

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

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

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

To solve this marginal probability equation, we use an expectation-maximization (EM) algorithm. EM algorithms are traditionally used to estimate LCCMs as described in depth in El Zarwi et al. (2017). A derivation of the EM algorithm can be found in Appendix A.

6.3.5) Model Selection

As noted in the literature, we could choose from a variety of joint models to simultaneously estimate the four sharing scenarios and find possible correlation. We opted against using a nested logit model since it would fail to capture the correlation between all scenarios. A nested logit model requires the modeler to develop a nest structure where the alternatives within a nest likely exhibit independence of irrelevant alternatives (IIA) properties and have similar unobserved attributes (Train, 2009). If we were to create a nested logit model, the two most appropriate nests would be partitioning the sheltering and transportation scenarios. However, this structure would only capture correlation within a nest, not between all scenarios. One potential solution would be to develop a cross-nested logit model, which can determine the extent of an alternative is part of two different nests. While some models have been developed (e.g., paired combinatorial logit) where each pair of alternatives can be built as a nest with correlation (Chu, 1989), such a structure requires at least one correlation scale parameter to be constrained.

We did not choose a discrete-continuous model or use structural equation modeling for our context since all variables were discrete (both require that at least one dependent variable be continuous) (Bhat, 2005; Ye et al., 2007). The simultaneous logit and simultaneous bivariate probit, were also not considered since they are formulated for only two choices (Ye et al., 2007). While a GEV-based logit regression has been developed for multiple choices, the research notes that its development is both analytically and computationally burdensome (Eluru et al., 2010). Overall, we chose to develop a portfolio choice model since it is a tractable, parsimonious model that does not require any hierarchical or sequential assumptions. The model has proven to handle small samples sizes (Chapter 7, Chapter 8) and can be easily estimated using basic discrete choice model packages without being computationally expensive. The model is also flexible, allowing for alteration of categories to suit the policy needs of agencies. We chose the multi-choice latent class choice model to explore unobserved classes of people based on lifestyle preferences or other characteristics. The estimation of classes (if present) differs significantly from other joint models and offers new behavioral nuances and insights. However, we note that one key limitation of this research is that we do not build all available models. We acknowledge that future research, including transportation areas beyond the present disaster sharing context, should begin more systematically developing multiple discrete choice models. This approach helps identify: 1) factors that are consistent across models, indicating behavioral stability, and 2) factors that are unique to the chosen model, revealing both benefits and limitations of the model structure.

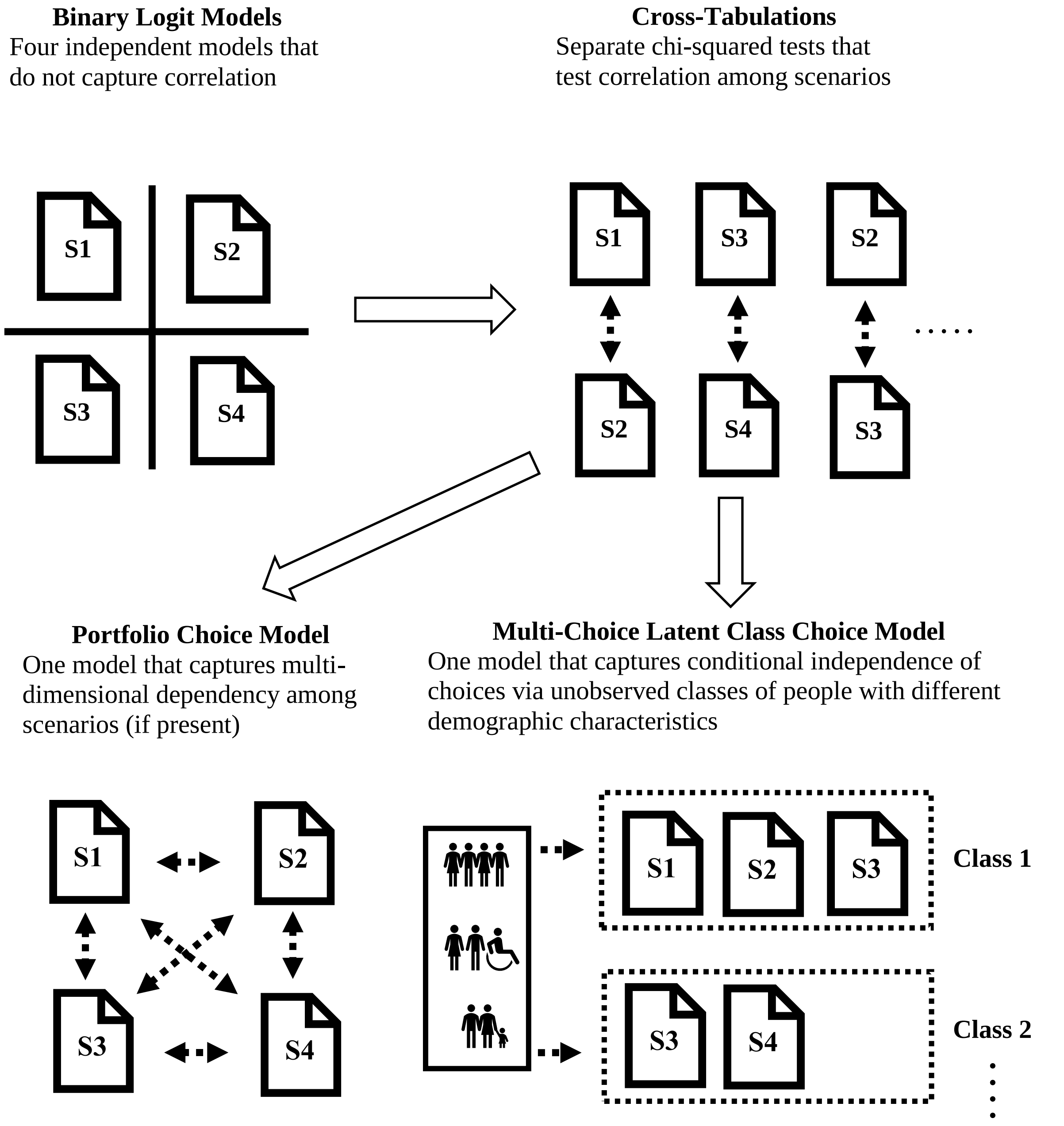
6.4) Results

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, seen graphically in Figure 1. We also conducted a series of cross-tabulations to determine if correlation was present among scenarios. We discuss the implications of each set of models and show the need to consider scenarios jointly.

6.4.1) Binary Logit Model Results

We first present the model results and a discussion of four independently constructed binary logit models. These models are not linked in any way and were developed separately to show the factors that impact willingness to share in each choice context.

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; and scenarios (i.e., choices) are known via the survey

6.4.1.1) Sharing Transportation Before – Binary Logit

For sharing transportation before evacuating, we found that individuals residing in Southwest Florida and households that evacuated with two or more vehicles during Hurricane Irma were more likely to share. Southwest Florida was heavily impacted by Hurricane Irma, and this very recent experience may drive individuals to consider sharing transportation to help others. Those with multiple vehicles likely had more flexibility in taking trips. For example, one vehicle could be packed, while the other vehicle could help provide trips prior to the evacuation. We found that additional seatbelts in the vehicle and evacuating within county to also be positive but insignificant. We found that households with children (i.e., families) and households living in the same residence for more than ten years were much less likely to share transportation before evacuating. Families have more items to pack and are highly concerned about their children's safety. Families may also depart earlier to protect their children, leaving little to help provide rides prior to evacuating. Long-time residents may be primarily concerned with protecting their property as they are typically less likely to evacuate (Riad et al., 1999; Wong et al., 2018b). Other negative (but insignificant) variables include young adults, females, high income households, and households with a person with a disability.

6.4.1.2) Sharing Transportation During – Binary Logit

During the evacuation, we did not find any significant variables that increased willingness to share. However, individuals residing in Southwest Florida, those with spare seatbelts in the vehicle, nighttime evacuees, and those who received a mandatory evacuation order were more likely to share (albeit insignificant). Again, Southwest Florida was severely impacted by Hurricane Irma, which may lead to first-hand experience of the need to provide transportation, particularly to carless individuals. Spare vehicle capacity is a pre-requisite for sharing, while nighttime evacuees may be less rushed and have more time to deviate from their route to pick someone up. Individuals who received a mandatory evacuation may have experienced urgency and may empathize with individuals in need of a ride. We also found that young adults, those with high experience in hurricanes, and individuals living in a mobile home were less likely to share. Young adults may not have vehicles to share and may lack overall evacuation experience, making them unknowledgeable of the needs of carless individuals. However, those with extensive experience may prioritize saving possessions over having extra space, especially if they had lost valuables in past events. Other insignificant and negative variables included high income households and towing something during the evacuation.

6.4.1.3) Sharing Shelter for a Cost – Binary Logit

We found that previous evacuees, households in a Federal Emergency Management Agency (FEMA) flood risk zone, those who have used homesharing before, and those with spare beds 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. Similarly, households in a FEMA risk zone may be highly cognizant of the challenges of finding shelter. Those with homesharing (e.g., Airbnb, VRBO) experience have knowledge of the sharing economy and can conceptualize sharing shelter in a disaster. Similar to seatbelts for transportation, spare beds are a prerequisite for sharing and help increase willingness to share. Positive but insignificant variables included females and those with household pets. We also found that white individuals, families, high income households, and homeowners were less likely to share shelter at a cost, but these variables were insignificant. Race may play a role in the perception of trust, a similar result to that of the discrimination of minorities in the sharing economy (Ge et al., 2016; Edelman et al., 2018). Families may again be concerned about the safety of their children, while high income households likely do not need additional money by charging for accommodations. Homeowners may be generally adverse to sharing their homes and may also not need extra money from evacuees. Several additional variables – young adults, residents of Southwest Florida, and those with older adults present in the household – were less likely to share shelter at a cost. These individuals may be generally unwilling to charge evacuees. Residents of Southwest Florida may assume that their home in a future disaster could be at risk and would choose to leave even they did not receive a mandatory evacuation order.

6.4.1.4) Sharing Shelter for Free – Binary Logit

Those who have used homesharing before were significantly more likely to share shelter for free. This is likely due to their experience with the sharing economy (e.g., Airbnb, VRBO). While insignificant, previous evacuees and those with spare beds were also more likely to share for free. White individuals and high income households were less likely to share, which may be tied to discrimination against evacuees in need of housing. Other insignificant variables – high hurricane experience, children present in the household, residents of Southwest Florida, households with a person with a disability, living in an apartment, and 1 or 2 person households – also decreased willingness to share shelter for free. High hurricane experience may be associated with a preference to be self-reliant, families may be concerned about safety, and residents of Southwest Florida may be unwilling to even stay in a future disaster. Households with a person with a disability may be mostly concerned with providing adequate healthcare. Residents of apartments and smaller households may lack the communal and bathroom space to shelter other evacuees, even if they have spare beds available.

Table 3: 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

	Sharing Transportation Before			**Sharing Transportation During**			**Sharing Shelter for Cost**			**Sharing Shelter for Free**		
Variable	**Est. Coef.**	**p-value**		**Est. Coef.**	**p-value**		**Est. Coef.**	**p-value**		**Est. Coef.**	**p-value**	
Constant Share	-0.66	0.162		-1.45	0.004	**	-2.83	0.004	**	-0.39	0.487	
Individual Characteristics												
Young Adult (under 35)	-0.44	0.117		-0.65	0.036	*	-0.45	0.254		-----	------	
Female	-0.43	0.166		-----	------		0.62	0.223		-----	------	
Experienced 3 or More Hurricanes	-----	------		-0.61	0.025	*	-----	------		-0.30	0.166	
White	-----	------		-----	------		-1.41	0.003	**	-0.81	0.029	*
Previous Evacuee	-----	------		-----	------		0.85	0.025	*	0.32	0.158	

Used Homesharing Before (e.g., Airbnb)	-----	------		-----	------		1.79	0.011	*	1.33	0.015	*
Household Characteristics												
Children Present in Household	-0.82	0.002	**	-0.42	0.115		-0.97	0.014	*	-0.31	0.334	
Residing in Southwest Florida	0.78	0.002	**	0.41	0.122		-0.35	0.378		-0.30	0.218	
Household Income $100,000 or More	-0.48	0.101		-0.32	0.297		-1.39	0.009	**	-0.49	0.041	*
Person(s) with Disabilities in Household	-0.46	0.202		-----	------		-----	------		-0.41	0.172	
More than 10 Years in Residence	-0.95	0.017	*	-----	------		-----	------		-----	------	
Living in a Mobile Home	-----	------		-1.15	0.059	†	-----	------		-----	------	
Elderly Present in Household	-----	------		-----	------		-0.65	0.219		-----	------	
Pet(s) Present in Household	-----	------		-----	------		0.51	0.247		-----	------	
Homeowner	-----	------		-----	------		-0.68	0.063	†	-----	------	
Live in FEMA Risk Zone [a]	-----	------		-----	------		0.74	0.041	*	-----	------	
Living in an Apartment	-----	------		-----	------		-----	------		-0.30	0.283	
1 or 2 Person Household	-----	------		-----	------		-----	------		-0.30	0.352	
Capacity												
Additional Seatbelts Available for Irma	0.38	0.309		0.65	0.121		-----	------		-----	------	
Additional Spare Beds in House	-----	------		-----	------		1.07	0.090	†	0.38	0.234	
Evacuation Experience During Irma												

Evacuated Within County	0.50	0.123		0.89	0.007	**	-----	------		-----	------
Evacuated with 2 or More Vehicles	0.53	0.066	†	-----	------		-----	------		-----	------
Towed a Vehicle	-----	------		-0.49	0.205		-----	------		-----	------
Evacuated at Night (6:00 pm - 5:59 am)	-----	------		0.45	0.201		-----	------		-----	------
Received a Mandatory Evacuation Order	-----	------		0.32	0.239		-----	------		-----	------
Observations	368			368			645			645	
R-squared	0.22			0.28			0.71			0.32	
Adjusted R-squared	0.18			0.23			0.68			0.30	
Log-Likelihood	-198.3			-183.8			-129.8			-303.3	
Null Log-Likelihood	-255.1			-255.1			-447.1			-447.1	

[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% †90%

6.4.1.5) Discussion of Binary Logit Models

Overall, we found a number of significant variables related to individual characteristics, household characteristics, and evacuation experience during Irma that significantly increased or decreased willingness to share transportation and shelter. We found that families and high income households were less likely to share across all scenarios. Young adults, individuals with high hurricane experience, white individuals, and households with a person with a disability were less likely to share across two or more scenarios. Residents of Southwest Florida were split: they were more likely to share transportation but less likely to share housing. Capacity (i.e., spare seatbelts or beds) increased willingness to share, but this was not always significant. Those who evacuated within county during Hurricane Irma were more likely to share transportation.

Despite these results, we found that the fit for the models (with the exception of sharing shelter for a cost) to be relatively low. Moreover, we found that there were not many significant variables for sharing transportation during the evacuation or sharing shelter for free. The results indicate that other mechanisms may be influencing individuals to share or not share. For example, individuals with strong social networks may be more willing to share resources (for example, Sadri et al., 2017a and Sadri et al., 2017b on the impact of social networks on evacuation choice). Other work has found that variables related to trust, compassion, and evacuation urgency were found to positively influence sharing behavior (Chapter 4). One key limitation to our survey is that we did not ask questions related to these variables.

Another key limitation of this analysis is that the models were developed separately. Indeed, we found that some variables influenced willingness to share in the same direction for some or all scenarios. Moreover, we would intuitively expect that those who would be willing to share transportation before the evacuation would likely be willing to share transportation during the evacuation. The same intuition could be applied to sharing shelter for a cost and free. This intuition is mostly due to the construction of the scenarios (which are relatively similar) but also due to the potential for people to be generally sharers or non-sharers. Our hypothesis that these scenarios are correlated in some way is confirmed by conducting a crosstabulation and chi-squared test of the different sharing scenarios (Table 4). While this analysis does not show the direction of influence, the table indicates that these scenarios (and real choices in a future evacuation) are linked. This suggests that developing separate and independent binary models inadequately assess behavior. Consequently, we developed and tested two different discrete choice models to better handle this correlation. The multi-choice LCCM connects the scenarios through a membership choice model (composed of demographic variables) and identifies classes of individuals who behave differently depending on the combination of scenarios. The PCM model determines interactions between choice dimensions (in this case the different scenarios) to uncover joint preferences and joint dislikes. Demographic variables are used to provide further precision of who is willing to share under each scenario. Together, the multi-choice LCCM and PCM tell a more nuanced story of the existing correlation.

Table 4: Visualization of a Series of Cross Tabulation Chi-Squared Results for Each Sharing Scenario with Associated p-value

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

	Sharing Transportation Before	Sharing Transportation During	Sharing Shelter for Cost	Sharing Shelter for Free
Sharing Transportation Before				
Sharing Transportation During	230.58 (<0.001***)			
Sharing Shelter for Cost	9.19 (<0.002**)	15.12 (<0.001***)		
Sharing Shelter for Free	26.53 (<0.001***)	33.85 (<0.001***)	31.61 (<0.001***)	

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

6.4.2) PCM Model Results

To explore this correlation among scenarios, we estimated a PCM as seen in Table 5. We provide results on a model with just primary dimensions and interactions and a model that includes demographic characteristics.

6.4.2.1) PCM Primary Dimensions and Interactions

In the first model, we first found that all four primary dimensions (i.e., the four scenarios) were strongly negative, which reflected the survey results in Table 1. We subsequently found two statistically significant interactions: 1) Transport Before and Transport During and 2) Shelter Cost and Shelter Free. While the correlation among these dimensions was expected based on the correlations in Table 4, the statistical significance in the joint preferences was high. Individuals had a joint preference for the transportation scenarios and a joint preference for the sheltering scenarios, which is likely due to the similarity in the resource type. 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.

Joint preference, especially for housing, could be leveraged to increase the number of individuals who offer their homes for free (at no cost to the evacuee). A strategy that does not incorporate fee-based sheltering will likely not suffer any meaningful drop in willingness to share resources. For transportation, joint preference indicates that people who are willing to share transportation before the evacuation are likely just as willing to provide transportation during the evacuation (and vice versa). This information allows agencies to easily encourage either action (or both) through a variety of communication mechanisms, thus increasing the number of resources provided and evacuation compliance. We also note that there was an insignificant joint preference between Transport During and Shelter Free. Finally, we found that even though strong correlation existed between all scenarios (Table 4), not all interactions were significant in the PCM. However, the interactions remained largely consistent even after demographic variables were added.

6.4.2.2) Share Transportation Before – PCM

For sharing transportation before evacuating, long-time residents and individuals with children were less willing to share. Length of residence may be connected with a general unwillingness to evacuate under most circumstances or a longer preparation time for securing a home. Children may require additional preparation time prior to evacuating, which limits the ability and time of parents to assist other individuals. Those residing in Southwest Florida were more likely to share, which is confirmed by the multi-choice LCCM and binary logit models. Low-income individuals were also more likely share transportation before evacuating, which could be tied to higher levels of empathy for carless individuals. Interestingly, those who towed an asset (i.e., another vehicle, trailer, boat) were more likely to share transportation before evacuating. Since the household had a long mobilization time, they have spare time to assist others (as long as their vehicle was available). Several evacuation circumstances (i.e., evacuating at night, receiving a mandatory evacuation order) decreased sharing likelihood, perhaps due to lowered mobilization time. The variable for spare seatbelts was not significant.

6.4.2.3) Share Transportation During – PCM

For sharing transportation during the evacuation, we found that families and long-time residents were more likely to share. It is not clear why families were more likely to share since all other models indicated otherwise. Long-time residents may have pre-scheduled trips to assist neighbors as they evacuate due to their strong social networks. Long-term residents also tend to travel shorter distances while evacuating (Wong et al., 2018b), which gives them time to deviate to pick up a passenger. Departing at night and evacuating within county were both positive. Adding extra time and evacuating within county indicate a convenience factor that impacts willingness to share. Indeed, those evacuating within county likely have more time to not only deviate from their route but also slightly longer evacuations that do not substantially increase their already short trip. At the same time, night evacuations tend to be less congested, which gives evacuees more time to deviate from their route. We found that those who received a mandatory evacuation order were more likely to share, indicating that urgency may trigger sharing behavior. On the hand, low-income individuals and those with items to tow were less likely to share. Low-income individuals may have less vehicle space (or no space if they are carless), while those with items to tow might consider that giving a ride only adds more burdens to the logistical challenges of protecting assets.

6.4.2.4) Share Shelter for a Cost – PCM

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 and opt against sharing shelter for a fee. Previous users of homesharing likely understand the mechanisms of the platforms and those who received a mandatory order may have experienced challenges finding their own housing. These experiential factors are important to consider, especially for areas that are not impacted by disasters on a regular basis or regions that are not well served by sharing economy companies. Additional capacity (spare beds/mattresses) increased willingness, but this was not significant. White individuals and families were less likely to share. Race may play a role in the perception of trust which could be a result of discrimination in the sharing economy (Ge et al., 2016; Edelman et al., 2018) and families may again be concerned about safety.

6.4.2.5) Share Shelter for Free – PCM

Finally, for shelter for free, we found that high-income individuals were more likely to share. These individuals do not need to charge a fee to shelter other evacuees, indicating some compassionate behavior. White individuals were still less likely to share, perhaps again due to a lack of trust. However, families were more likely to share shelter for free. We note that families may be more likely to share for free as they may have empathy for other families. We also found two semi-strong variables, while not statistically significant, that did have a correct sign – low-income households and previous users of homesharing (both positive). Low-income households may exhibit stronger charitable behavior and have empathy for others in need of shelter. Previous homesharing users have experience with platforms that would connect hosts and guests. Receiving a mandatory evacuation order led to less sharing for free (the opposite result of sharing shelter cost). This result is not immediately explainable but could be associated with a need to regain income after taking a financial loss from Hurricane Irma.

Table 5: PCM Results

Variables	Primary + Interactions Est. Coef.	Primary + Interactions p-value		Primary + Interactions + Demographics Est. Coef.	Primary + Interactions + Demographics p-value	
Primary Dimensions						
Share Transport Before	-2.38	<0.001	***	-2.50	<0.001	***
Share Transport During	-4.20	<0.001	***	-6.52	<0.001	***
Share Shelter Cost	-3.75	<0.001	***	-4.70	0.001	***
Share Shelter Free	-2.06	<0.001	***	-2.12	0.004	**
Interactions						
Transport Before x Transport During	4.97	<0.001	***	6.70	<0.001	***
Transport Before x Shelter Cost	-0.13	0.905		-0.19	0.851	
Transport Before x Shelter Free	0.47	0.355		0.64	0.227	
Transport During x Shelter Cost	1.15	0.285		0.98	0.338	
Transport During x Shelter Free	1.01	0.051	†	1.03	0.056	†
Shelter Cost x Shelter Free	1.88	<0.001	***	2.00	<0.001	***
Transport Before Variables						
Children Present in Household	-----	------		-1.48	0.001	***
Residing in Southwest Florida	-----	------		1.49	0.001	***
Annual Household Income Below $40,000	-----	------		1.14	0.062	†
Annual Household Income $100,000 or Above	-----	------		0.22	0.661	
Living in Residence for 10+ Years	-----	------		-2.90	0.001	***
Additional Seatbelts Available for Irma	-----	------		-0.10	0.858	
Evacuated Within County During Irma	-----	------		-0.28	0.631	
Towed an Item During Irma	-----	------		0.91	0.091	†
Evacuated at Night During Irma (6:00 pm - 5:59 am)	-----	------		-0.91	0.175	
Received Mandatory Evacuation Order During Irma	-----	------		-0.52	0.241	
Transport During Variables						
Children Present in Household	-----	------		0.82	0.095	†
Residing in Southwest Florida	-----	------		-0.78	0.105	
Annual Household Income Below $40,000	-----	------		-1.49	0.026	*
Annual Household Income $100,000 or Above	-----	------		-0.48	0.365	
Living in Residence for 10+ Years	-----	------		2.27	0.009	**
Additional Seatbelts Available for Irma	-----	------		0.76	0.235	
Evacuated Within County During Irma	-----	------		1.06	0.072	†
Towed an Item During Irma	-----	------		-1.22	0.036	*
Evacuated at Night During Irma (6:00 pm - 5:59 am)	-----	------		1.20	0.073	†
Received Mandatory Evacuation Order During Irma	-----	------		0.87	0.066	†
Shelter Cost Variables						
White (race)	-----	------		-0.95	0.196	
Children Present in Household	-----	------		-0.82	0.117	
Annual Household Income Below $40,000	-----	------		0.44	0.501	
Annual Household Income $100,000 or Above	-----	------		-1.03	0.065	†
Additional Spare Beds in House	-----	------		1.75	0.103	
Used Homesharing Before (e.g., Airbnb)	-----	------		1.99	0.017	*
Received Mandatory Evacuation Order During Irma	-----	------		1.27	0.023	*
Shelter Free Variables						
White (race)	-----	------		-0.73	0.191	

Children Present in Household	-----	------	0.63	0.041	*
Annual Household Income Below $40,000	-----	------	0.56	0.235	
Annual Household Income $100,000 or Above	-----	------	0.69	0.058	†
Additional Spare Beds in House	-----	------	0.11	0.779	
Used Homesharing Before (e.g., Airbnb)	-----	------	1.09	0.132	
Received Mandatory Evacuation Order During Irma	-----	------	-0.49	0.103	
Observations	368		368		
Parameters	10		44		
R-Squared	0.44		0.50		
Adjusted R-Squared	0.43		0.45		
Log-Likelihood	-545.4		-490.5		
Log-Likelihood Null	-971.2		-971.2		
AIC	1110.7		1069.1		
BIC	1149.8		1241.0		

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

6.4.3) Multi-Choice LCCM Model Results

We next present the results of the multi-choice LCCM model (Table 6) via four choice models and one membership model that connects the choice models together. We tested several variables to be included in the choice-specific models (e.g., receiving a mandatory evacuation order, spare beds), but we only found spare seatbelts to be significant in impacting transportation choices. 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. Moreover, we found three distinct classes of individuals with different characteristics, indicating that two classes were inadequate to explain behavior.

6.4.3.1) 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 more room to pack additional belongings when evacuating. 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). Families were more likely to be in Class 1 as compared to the other two classes, which indicates their preference for not sharing. As noted in the binary logit models, this may be influenced by their primary concerns of protecting their family.

6.4.3.2) Class 2 – Transportation Sharers

This class of individuals was generally willing to share transportation both before and during an evacuation, hence a class of “transportation sharers.” The constants for Class 2 in the transportation scenarios were both positive, but only sharing transportation before was significant. Additional seatbelts also increased willingness to share for this class, indicating that capacity was a driving factor to share. Moreover, this class exhibited strong aversion to sharing shelter, as seen with the negative and significant Class 2 constants for both sheltering scenarios. Membership into Class 2 was largely composed of residents from Southwest Florida, females, and low-income households (under $40,000 per year). As noted in the binary logit models, individuals from Southwest Florida were heavily impacted by Hurricane Irma and this experience of needing to evacuate communities may have led some to want to share in a future disaster. Moreover, residents may have witnessed firsthand the challenges of evacuating carless individuals. Females may be more willing to be transportation sharers since this type of assistance is largely temporary (compared to long-term housing). We note, however, that the result counters our binary logit models that found either lower willingness or no impact of females on sharing transportation. We hypothesize that the correlation of the scenarios impacted this difference. Finally, low-income individuals may be more willing to share transportation since they recognize the needs of carless individuals. This potential empathy again points to the need to include more social network, trust, and compassion variables.

6.4.3.3) Class 3 – Interested Sharers

This class of individuals was general more willing to share resources across all scenarios but the constants across scenarios were insignificant in most cases. However, Class 3 exhibited stronger sheltering sharing behavior. Thus, Class 3 might be considered a "interested sharers" class in that they might share in a future disaster, but some concerns may be holding them back from actually choosing to share. Additional seatbelts increased willingness to share, but it was not as strong of an influencer compared to Class 2 (Transportation Sharers). Individuals living in their residence for more than 10 years were more likely to belong to Class 3 as compared to Class 1. Long-time residents may have stronger social networks and know more people who could need assistance. At the same time, long-time residents may prefer to be self-reliant and focus on their own needs. These conflicting reasons may contribute to the "interested sharers" class. Individuals in this class were also more likely to higher-income, male, living without children, and residing outside of Southwest Florida (as compared to Class 1). Higher-income individuals have resources to share but often prefer to travel further away and would not be able to share. Males tend to be less concerned about safety, but they might also not have as high empathy or compassion. Households without children do not have protection concerns, but they may also have less resources. Finally, those outside of Southwest Florida may have more available resources and less hurricane risk, but they also lack experience in evacuations and disaster relief.

Table 6: Multi-Choice LCCM 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 Under $40,000 - Class 2	0.05	0.088	†
Annual Household Income Under $40,000 - Class 3	-0.97	0.110	
Number of Observations	368		
Number of Parameters	30		
AIC	1131.8		
BIC	1249.0		
Final Log-Likelihood	-535.9		

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

6.4.4) Modeling Discussion

Through our modeling exploration of the willingness to share resources, we found distinct benefits and limitations of each model type. We began our modeling using simple binary logit models, which allowed us to focus on each scenario (i.e., choice situation) separately. These models have the benefit of identifying specific provider groups for a single scenario without influence from other scenarios. This division is helpful for agencies if they want to focus on a single sharing strategy (i.e., transportation during evacuating). For example, families with children, people living in mobile homes, and those with significant hurricane experience were less likely to share transportation during the evacuation. Agencies could pilot a sharing economy strategy in downtown or high-density neighborhoods, where more households tend to have recently moved in and do not have children. However, this simplicity belies the correlation that is present in the different scenarios. The cross tabulation of the scenarios (Table 4) displays clear correlation. We note that this result is encouraging for public agencies, since the development of a mechanism to share transportation before an evacuation would likely encourage individuals to share transportation during the evacuation. The correlation also indicates that sharing willingness is related across different resource types (i.e., transportation and shelter). Agencies could gain efficiency in promoting sharing as a holistic concept across resource types the disaster timeline rather than separate actions at single points in time.

After identifying existing correlation, we explored two joint discrete choice models: 1) PCM and 2) a multi-choice LCCM. Easy to construct and estimate as a multinomial logit model, the PCM was able to identify correlation between scenarios (solving the primary issue with the binary logit models). The model was also able to clearly define provider groups of shared resources (similar to the binary logit models). However, we found that the inclusion of more parameters in the PCM, while mostly significant, did not improve the overall fit of the model. We also note that several results from the PCM were different from the binary logit models, indicating a complex correlation structure. The PCM also fails to identify classes of individuals, which diminishes a more holistic understanding of groups of people and their willingness to share.

With this major limitation for the PCM, a multi-choice LCCM was constructed to connect the different scenarios through the membership model, which allowed us to identify 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. Even small improvements in a sharing framework could push people to share. Despite these more nuanced results over the binary logit models, we do lose some details of provider groups due to the multi-choice LCCM structure. The multi-choice LCCM is also sensitive to a high parameter to sample size ratio. In the development process, we found that the inclusion of choice-specific variables (i.e., spare beds, mandatory evacuation orders) were insignificant and would lead to additional insignificance in the membership model. We also found the model to be highly sensitive to the number of latent classes. We settled on three latent classes as each class was clearly defined. However, two latent classes did not provide enough behavioral nuance and four classes led to poorly defined classes.

Several key takeaways could be gleaned from the behavioral results when looking at the models together. 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 two resource types. Second, families were unwilling to share. In almost all models and scenarios, families were less willing to provide resources. This results likely stems from concerns about their childrens' safety and security, which was also found in Chapter 3. Third, spare capacity had positive but largely insignificant influence on sharing. Across the models, spare capacity (i.e., seatbelts, spare beds) variables were not powerful in impacting willingness to share. While capacity is a prerequisite for sharing, it is not a primary motivator for why people would be willing to share in an evacuation. Fourth, income had uneven impacts on willingness to share. Variables for low-income and high-income individuals did not have clear directionality on the willingness to share. This indicates that other variables unrelated to resources may be impacting sharing (e.g., compassion, trust, social capital). 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. Sixth, transportation sharing was driven by different factors – spare capacity, individual characteristics, household characteristics, evacuation circumstances – but the significance was not consistent across models or scenarios. Similar to sharing shelter, transportation sharing may be more consistently impacted to trust and compassion. The results also suggest that transportation sharing may be context-dependent and that the decision to actually share may require a triggering mechanism, which was found for wildfire evacuations (Chapter 4).

Finally, most demographic variables were somewhat weak and sporadic indicators of sharing. Across all the models, we found significant variation on which demographic variables were important factors, along with their direction of influence. This "non-result" indicates that variables more related to social capital, such as trust, compassion, and social network, may be stronger drivers of sharing behavior. Very recent work in Chapter 4 found that trust and compassion along with variables related to evacuation urgency were the important indicators for willingness to share for future wildfires. Wong and Shaheen (2019) found that vulnerable populations tended to distrust drivers, hosts, and sharing economy companies, which would make them less likely to use shared resources in a disaster. Other work including Sadri et al., (2018) found that social capital and social networks were important factors in post-disaster recovery and resilience. Evidence in Sadri et al. (2017a) and Sadri et al. (2017b) indicate that social networks also play a role in general evacuation decision-making. These studies taken together, along with this work, suggests that increasing shared resources in disasters should focus more on internal motivations for sharing, not demographic characteristics.

6.5) Recommendations and Conclusion

Finally, we present several recommendations based on the modeling results. We note that these recommendations are largely intuitive. However, the models offer empirically based evidence to further a sharing economy strategy for disaster response and relief.

Recommendation: A transportation sharing strategy should not be constrained temporally and should allow individuals to share before, during, and after the disaster. For transportation before and during the evacuations, agencies will need multiple communication mechanisms (e.g., mobile phone, Internet, landlines, neighborhood networks) to reach that those in need of rides can be properly matched with providers. Agencies will also need to ensure that drivers are safe and do not enter a hazardous area.

> Evidence: Modeling results indicate significant correlation between transporting passengers before and during the evacuation, which could increase willingness to share for either scenario. For example, an individual who may be willing to share before evacuating but is unable due to evacuation circumstances may still share during or after the evacuation. Past literature has suggested that TNCs focus mostly on disaster relief and recovery, indicating an opportunity after the disaster.

Recommendation: A sheltering sharing strategy should be free for evacuees. This may place a small administrative cost on the agency or company running the matching algorithm. Similar to transportation, agencies will need multiple communication mechanisms (e.g., mobile phone, Internet, landlines, neighborhood networks) to properly matched users and providers.

> Evidence: Modeling results indicate that willingness to share shelter for a cost and for free are highly correlated. In addition, more individuals are willing to share shelter for free.

Consequently, a free strategy (such as the Airbnb Open Homes Program) will not experience a noticeable drop in willingness. A free sheltering strategy would also make housing more accessible for evacuees, regardless of income.

Recommendation: Agencies should consider combining a transportation strategy and a sheltering strategy into a holistic program. The program should be constructed and advertised as an evacuee assistance program that offers multiple opportunities for people to volunteer and assist.

Evidence: Bivariate correlation was present across all scenarios and the PCM found mostly positive interactions among scenarios, indicating joint preference. The multi-choice LCCM found a class of interested sharers who were somewhat more willing to share resources across all scenarios. These results taken together suggest that transportation and sheltering could be considered together as a bundle. A more holistic program would help encourage individuals who are sharing interested. Moreover, a more comprehensive program could nudge interested sharers to provide other resources beyond transportation and sheltering such as food, supplies, or even direct monetary assistance.

Recommendation: Agencies should focus on outreach to households without children in a sharing strategy. Outreach about an evacuation assistance program could be conducted via an online or mailing campaign. Other characteristics of the household (i.e., income, residence structure type, age of members) should not be considered for targeted outreach.

Evidence: Households with children were significantly less willing to share resources across most scenarios, which is likely due to safety concerns and placing the highest priority on children. Targeted outreach to encourage people to share resources should focus on households without children. However, without clear modeling results for other household characteristics, any campaign or program should not target any other specific household characteristic until further and consistent empirical evidence is found.

Recommendation: Agencies should partner with and leverage existing homesharing platforms (e.g., Airbnb, VRBO) to increase willingness to share sheltering. Both hosts and users of homesharing should be encouraged to provide shelter to evacuees.

Evidence: Users of homesharing were more willing to share shelter in the binary logit models and the PCM. While the current Airbnb Open Homes Program only encourages hosts to provide shelter, a future sheltering strategy should also contact and encourage regular or long-time users of homesharing. These individuals likely understand the homesharing process and would use this experience to help others in a disaster.

In this study, 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) – using data from individuals who were impacted by Hurricane Irma in 2017. These models revealed the factors that impacted willingness to share transportation and sheltering resources across four scenarios. We first constructed four binary logit models to independently assess how demographic variables, household characteristics, spare capacity, and evacuation circumstances impacted each scenario separately. However, we hypothesized that the responses to the sharing scenarios were correlated, which we found through a simple bivariate cross-tabulation. To handle this correlation, we first developed PCM that could identify dimensional dependency between scenarios. We found strong joint preferences through the PCM, particularly between the transportation scenarios and between the shelter scenarios. We found some overlap between the binary logit and PCM models on the demographic variables that impacted willingness to share, but these results were largely inconclusive. The results suggest that other variables, such as compassion and trust, may be driving willingness to share.

We next developed a multi-choice LCCM, which captures classes of individuals across multiple choices through a single membership model of demographic characteristics. We found three unique classes of individuals: 1) adverse sharers, 2) interested sharers, and 3) transportation-only sharers. Each class had different likelihoods to share across the four scenarios and were composed of different demographics, indicating the presence of unique provider groups. Compared to adverse sharers, transportation sharers were more likely to be female, lower-income, and residents of Southwest Florida. The temporary nature of sharing transportation, empathy for others with resource deficiencies, and the trigger of Hurricane Irma may be leading to these results. Also compared to adverse sharers, interested sharers were more likely to be male, long-time residents, and higher-income. These individuals may prioritize other actions (i.e., protecting family members, protecting property) before choosing to share resources. However, these demographic variables were somewhat weak in impacting class membership, which mirrors the weak demographic results in the binary logit models and the PCM. Altogether, this multi-model analysis using three different discrete choice model forms uncovered behavioral nuances and more conclusive results than if a single model had been developed. Moreover, this process of employing multi-models encourages exploration of the benefits and limitations of different models, without assuming superiority of one model over another.

This research also represents a key step into building a sharing economy framework for disasters. While spare capacity is needed before someone can share, the modeling results suggest that additional behavioral nudges are likely needed by public agencies to encourage sharing behavior and implement an effective sharing economy strategy for hurricane evacuations. For example, public agencies could alleviate concerns related to safety and security by developing a matching structure that uses neighborhood networks, rather than matching strangers with other strangers. In a small action, public agencies could nudge people to share by indicating in mandatory evacuation orders that people should check on their neighbors and assist if possible. In addition, rather than focus on single temporal points in a disaster or separate resource types, agencies should consider build a more holistic sharing program that can be leveraged before, during, and after a disaster. Moreover, this sharing program should encourage sharing for all resource types, since a person that is willing to share transportation is also somewhat likely to also share sheltering. The research also indicates that other variables, perhaps related to social networks, trust, and compassion, may be more impactful on the willingness to share than demographic variables. Despite these somewhat inconclusive results, this work still encourages the use of multiple models including the use of PCMs and multi-choice LCCMs to assess multiple choice contexts apart from evacuations.

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6.7) Appendix

6.7.1) Expectation-Maximization (EM) Algorithm Derivation

To estimate the marginal probability equation for the multi-choice LCCM equation, we derive an expectation-maximization (EM) algorithm which will solve this problem. We first write out the probabilities into their respective logit kernels.

$$P(\boldsymbol{y}^m) = \prod_{n=1}^{N}\sum_{s=1}^{S}\left[\frac{\exp(z'_{ns}\tau_s)}{\sum_{s'=1}^{S}\exp\left(z'_{ns'}\tau_s\right)}\prod_{m=1}^{M}\prod_{i\in C_m}\left[\frac{\exp(x'_{nmi}\beta_s)}{\sum_{i'=1}^{|C|}\exp(x'_{nmi}\beta_s)}\right]^{y_{ni}^m}\right]$$

The EM algorithm first begins by making the assumption that (q_{ns}) is observable. With this assumption, we rewrite the probability equation as a likelihood function.

$$L_c = \left(\prod_{n=1}^{N}\prod_{s=1}^{S}\left[\frac{\exp(z'_{ns}\tau_s)}{\sum_{s'=1}^{S}\exp\left(z'_{ns'}\tau_s\right)}\right]^{q_{ns}}\right)\left(\prod_{n=1}^{N}\prod_{s=1}^{S}\prod_{m=1}^{M}\prod_{i\in C_m}\left[\frac{\exp(x'_{nmi}\beta_s)}{\sum_{i'=1}^{|C|}\exp\left(x'_{nmi'}\beta_s\right)}\right]^{y_{ni}^m q_{ns}}\right)$$

$$LL_c = \sum_{n=1}^{N}\sum_{s=1}^{S}q_{ns}\log\left[\frac{\exp(z'_{ns}\tau_s)}{\sum_{s'=1}^{S}\exp(z'_{ns}\tau_s)}\right] + \sum_{n=1}^{N}\sum_{s=1}^{S}\sum_{m=1}^{M}\sum_{i\in C_m}\boldsymbol{y}_{ni}^m q_{ns}log\left[\frac{\exp(x'_{nmi}\beta_s)}{\sum_{i'=1}^{|C|}\exp(x'_{nmi}\beta_s)}\right]$$

The two vectors that need to be estimated are τ and β_s and we can use the knowledge that q_{ns} is observable (or at least "filled in"). We take the log of the likelihood function to get log-likelihood.

6.7.1.1) E-Step

In the E-step, we need to estimate the expectation of the latent variable q_{ns}. In this case, we are interested in the expectation when the latent variable is equal to 1 (allocated to the latent class). We simplify notation by denoting a new single vector θ which is composed of τ_s and β_s.

$$E[q_{ns}|\boldsymbol{y}^m;\theta] = P(q_{ns} = 1 \mid \boldsymbol{y}^m;\theta)$$

Note that this probability can also be expressed as $LL(q,\theta)$. Using Bayes Rule, we rewrite this equation into known parts.

$$E[q_{ns}|\boldsymbol{y}^m;\ \theta] = \frac{P(\boldsymbol{y}^m|q_{ns} = 1;\theta)\ \times P(q_{ns} = 1|\theta)}{P(\boldsymbol{y}^m|\theta)}$$

We now note how the EM algorithm is an iterative process through which parameter estimates (currently in the form of θ) are updated with each iteration. An update is noted as $(t+1)$. The expectation the latent variable can be described as:

$$q_{ns}^{(t+1)} = argmax\ L\left(q,\theta^{(t)}\right)$$

$$q_{ns}^{(t+1)} = \frac{P\left(\boldsymbol{y}^m \middle| q_{ns} = 1; \theta^{(t)}\right) \times P\left(q_{ns} = 1 \middle| \theta^{(t)}\right)}{P\left(\boldsymbol{y}^m \middle| \theta^{(t)}\right)}$$

We replace these probabilities with their values from the log-likelihood function.

$$P\left(\boldsymbol{y}^m \middle| q_{ns} = 1; \theta^{(t)}\right) = \prod_{n=1}^{N}\prod_{m=1}^{M}\prod_{i \in C_m}\left[\frac{\exp\left(x'_{nmi}\beta_s^{(t)}\right)}{\sum_{i'=1}^{|C|}\exp\left(x'_{nmi'}\beta_s^{(t)}\right)}\right]^{\boldsymbol{y}_{ni}^m}$$

$$P\left(q_{ns} = 1 \middle| \theta^{(t)}\right) = \prod_{n=1}^{N}\frac{\exp\left(z'_{ns}\tau^{(t)}\right)}{\sum_{s'=1}^{S}\exp\left(z'_{ns'}\tau^{(t)}\right)}$$

$$P\left(\boldsymbol{y}^m \middle| \theta^{(t)}\right) = \prod_{n=1}^{N}\sum_{s=1}^{S}\left[\frac{\exp\left(z'_{ns'}\tau^{(t)}\right)}{\sum_{s'=1}^{S}\exp\left(z'_{ns'}\tau^{(t)}\right)}\prod_{m=1}^{M}\prod_{i \in C_m}\left[\frac{\exp\left(x'_{nmi}\beta_s^{(t)}\right)}{\sum_{i'=1}^{|C|}\exp\left(x'_{nmi'}\beta_s^{(t)}\right)}\right]^{\boldsymbol{y}_{ni}^m}\right]$$

Our final E-step in full form is as follows:

$$q_{ns}^{(t+1)} = \frac{\prod_{n=1}^{N}\prod_{m=1}^{M}\prod_{i \in C_m}\left[\frac{\exp\left(x'_{nmi}\beta_s^{(t)}\right)}{\sum_{i'=1}^{|C|}\exp\left(x'_{nmi'}\beta_s^{(t)}\right)}\right]^{\boldsymbol{y}_{ni}^m} \times \prod_{n=1}^{N}\frac{\exp\left(z'_{ns}\tau^{(t)}\right)}{\sum_{s'=1}^{S}\exp\left(z'_{ns'}\tau^{(t)}\right)}}{\prod_{n=1}^{N}\sum_{s=1}^{S}\left[\frac{\exp\left(z'_{ns'}\tau^{(t)}\right)}{\sum_{s'=1}^{S}\exp\left(z'_{ns'}\tau^{(t)}\right)}\prod_{m=1}^{M}\prod_{i \in C_m}\left[\frac{\exp\left(x'_{nmi}\beta_s^{(t)}\right)}{\sum_{i'=1}^{|C|}\exp\left(x'_{nmi'}\beta_s^{(t)}\right)}\right]^{\boldsymbol{y}_{ni}^m}\right]}$$

6.7.1.2) M-Step

The M-step maximizes the parameter vectors based on the value of $q_{ns}^{(t+1)}$ which was found in the E-step. This value is treated as the "true" value which allows us to maximize the log-likelihood function.

$$\theta_{ns}^{(t+1)} = argmax\ LL\left(q^{(t+1)}, \theta\right)$$

We can split this expression into the separate class-specific and class-membership estimable vectors, and estimate the parameters based on the following equations.

$$\beta_s^{m,(t+1)} = argmax\ \sum_{n=1}^{N}\sum_{s=1}^{S}\sum_{i \in C_m} y_{ni}^m q_{ns}^{(t+1)} log\left[\frac{\exp\left(x'_{nmi}\beta_s^{m,t}\right)}{\sum_{i'=1}^{|C|}\exp\left(x'_{nmi'}\ \beta_s^{m,t}\right)}\right]$$

$$\tau^{(t+1)} = argmax\ \sum_{n=1}^{N}\sum_{s=1}^{S} q_{ns}^{(t+1)} \log\left[\frac{\exp(z'_{ns}\tau)}{\sum_{s'=1}^{S}\exp(z'_{ns}\tau)}\right]$$

6.7.2) Appendix Tables

Table A1: Demographic Characteristics of Hurricane Irma Survey Respondents (n=645)

Evacuation Choice	
Received Mandatory Order, Evacuated	69.5%
Received Mandatory Order, Stayed	30.5%
No Mandatory Order, Evacuated	46.4%
No Mandatory Order, Stayed	53.6%
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%
Live in FEMA* Flood Risk Area	
Yes	39.5%
No	47.9%
I don't know	12.6%
* Federal Emergency Management Agency	
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%
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%
More than $150,000	12.4%
No/prefer no answer	11.8%
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%
Household Characteristics	
Household with Disabled	16.4%
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%
Pacific Islander	0.2%
Native American/Alaska Native	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%
2-year degree	12.9%
4-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%
Primary Transportation Mode for Work/School	
Drive alone using automobile	94.3%
Work from home	1.7%
Carpool/vanpool	0.9%
Bus	0.8%
Bicycle	0.6%
Motorcycle/scooter	0.3%
Walk	0.3%

Household with Children	44.8%	Shared mobility	0.2%
Household with Elderly	15.0%	Rail	0.0%
Households with Pets	77.1%	Other	0.9%
Access to Internet at Home		**Previous Hurricanes Experienced**	
Yes	98.3%	0	3.6%
No	1.7%	1 or 2	31.3%
		3 or 4	17.5%
Mobile Phone Type		5 or more	47.6%
Own a smartphone	96.3%		
Own a non-smartphone	3.4%	**Previous Evacuations Experienced**	
Do not own a cell phone	0.3%	0	46.4%
		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%

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Chapter 7: Fleeing from Hurricane Irma: Empirical Analysis of Evacuation Behavior Using Discrete Choice Theory

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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

7.1) 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., 2013), 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.

7.2) 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.

7.3) 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.

7.3.1) 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.

7.4) 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

<u>Categories for Cross Tabulations</u>
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, bike)

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., 2nd 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

7.4.1) 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.

7.4.2) PCM Primary Variables + Interactions

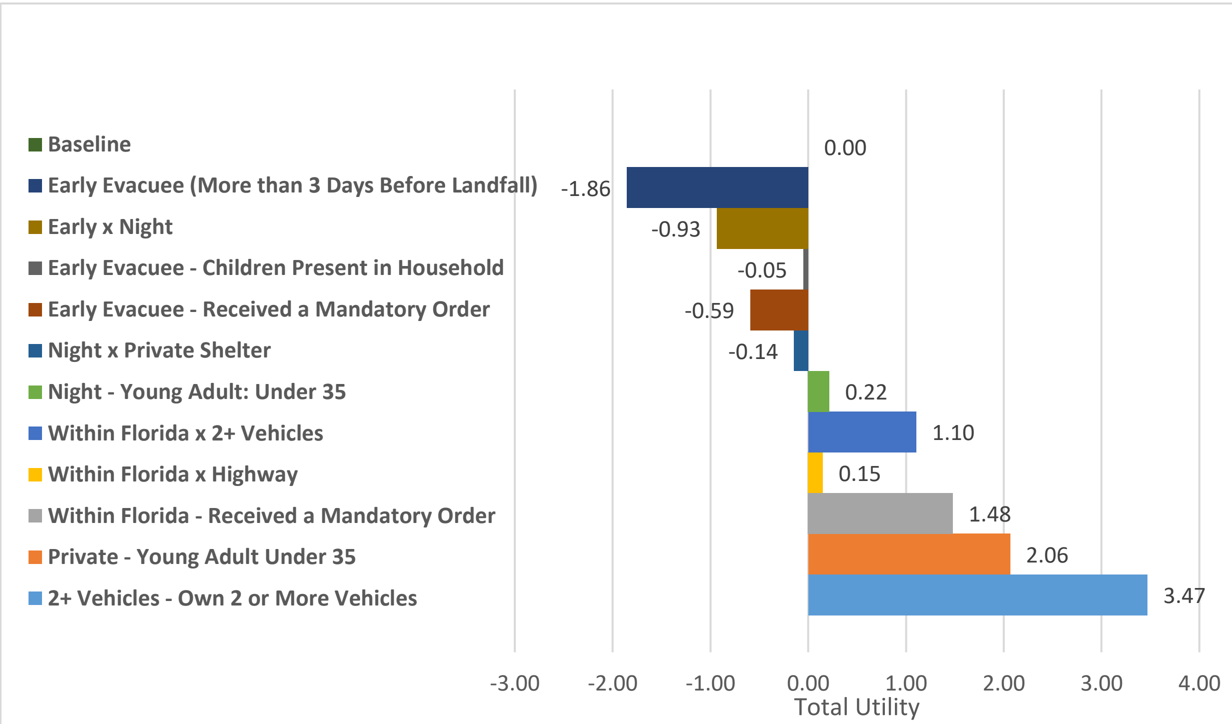
To build a more insightful model with more explanatory power, we considered the impact of primary variable interactions. With the addition of interaction effects, variables for regular time evacuees and highway evacuees became insignificant, while the early evacuee variable became significant. Some primary 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.

7.4.3) 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.

7.4.4) 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).

7.5) 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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7.7) Appendix

7.7.1) 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:

$$U_{ni|s} = V_{ni|s} + \varepsilon_{ni|s} \tag{1}$$

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:

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

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:

$$P(q_{n1}|Z_n) = \frac{\exp\,(\gamma' Z_n)}{1+\exp\,(\gamma' Z_n)} \quad (3)$$

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

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

7.7.2) Appendix Tables

Table A1: Household and Individual Respondent Demographics

Gender		**County of Residence**	
Female	81.9%	Brevard	53.2%
Male	18.1%	Lee	17.2%
		Collier	13.3%
Age		Miami-Dade	3.7%
18-24	3.1%	Pinellas	2.9%
25-34	26.0%	Monroe	2.6%
35-44	28.7%	Broward	2.5%
45-54	21.7%	All other counties	4.5%
55-65	14.9%		
65+	5.6%	**Distance from Major Water Source**	
		Next to Major Source	15.3%
Race		1 mile	16.4%
White	94.0%	2 to 4 miles	20.7%
Black or African-American	1.6%	5 to 9 miles	23.6%
Mixed	1.1%	10 to 20 miles	17.8%
Asian	0.9%	Over 20 miles	3.6%
Native American/Alaska Native	0.2%	No answer	2.6%
Pacific Islander	0.2%		
No answer/Prefer no answer	2.2%	**Residence Structure**	
		Site build (single home)	76.6%
Ethnicity		Site build (apartment)	19.1%
Not Hispanic	89.5%	Mobile/manufactured home	4.3%

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%

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%

In-Vehicle/Smartphone Navigation	
Yes	87.9%
No	12.1%

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%

Household Characteristics	
Household with Disabled	16.4%
Household with Children	44.8%
Household with Elderly	15.0%
Households with Pets	77.1%

Annual 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%

Access to Internet at Home	
Yes	98.3%
No	1.7%

* 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)*	100% 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%
Alabama	4.9%
South Carolina	3.5%
Virginia	2.4%
Louisiana	1.6%
Mississippi	1.6%
Ohio	1.6%
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	
*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%

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%
Note: Rounding may cause choices to not exactly equal 100%		After Sunday, Sept. 17	9.8%

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

7.8) References

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Chapter 8: Understanding California Wildfire Evacuee Behavior and Joint Choice Making

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ABSTRACT

For evacuations, people must make the critical decision to evacuate or stay followed by a multi-dimensional choice composed of concurrent decisions of their departure time, transportation mode, route, destination, and shelter type. These choices have important impacts on transportation response and evacuation outcomes. While extensive research has been conducted on hurricane evacuation behavior, little is known about wildfire evacuation behavior. To address this critical research gap, particularly related to joint choice making in wildfires, we surveyed individuals impacted by the 2017 December Southern California Wildfires (n=226) and the 2018 Carr Wildfire (n=284). Using these data, we contribute to the literature in two key ways. First, we develop two simple binary choice models to evaluate and compare the factors that influence the decision to evacuate or stay. Mandatory evacuation orders and higher risk perceptions both increased evacuation likelihood. Individuals with children and with higher education were more likely to evacuate, while individuals with pets, homeowners, low-income households, long-term residents, and prior evacuees were less likely to evacuate. Second, we develop two portfolio choice models (PCMs), which jointly model choice dimensions to assess multi-dimensional evacuation choice. We find several similarities between wildfires including a joint preference for within-county and nighttime evacuations and a joint dislike for within-county and highway evacuations. To help build a transportation toolkit for wildfires, we provide a series of evidence-based recommendations for local, regional, and state agencies. For example, agencies should focus congestion reducing responses at the neighborhood level within or close to the mandatory evacuation zone.

Keywords: Evacuations, evacuee behavior, California wildfires, portfolio choice model

8.1) Introduction

In recent years, the United States (US), in particular California, has been impacted by multiple devastating wildfires that have caused mass evacuations. Between 2017 and 2019, 100,000 or more people were ordered to evacuate from five wildfires (see Table 1). Meanwhile, at least 10,000 people were ordered to evacuation from an additional six wildfires over the same time period. Despite these recent large-scale events, little is known about the decisions that individuals make in wildfire evacuations, particularly in a US context. Individuals must first decide if they will evacuate or stay in a wildfire evacuation, which is complicated by defending behavior where individuals will attempt to save their home by fighting the fire (McCaffrey and Rhodes, 2009; McCaffrey and Winter, 2011 Paveglio et al., 2012). Some recent work has been conducted using discrete choice analysis to understand actual behavior in wildfires in Israel (Toledo et al., 2018), fire-prone areas of the United States (McCaffrey et al., 2018), and Australia (Lovreglio et al., 2019). However, no work to date has employed discrete choice methods and revealed preference data to assess the decision to evacuate or stay in a California context. Moreover, it remains unclear if factors in other countries are transferable to the US and California

If an individual decides to evacuate, they are then faced with a complex and multi-dimensional choice composed of departure time, transportation mode, route, destination, and shelter type. These choices, which may exhibit correlation, have been only minimally studied in wildfire evacuations. While work has been conducted to assess joint choice making in hurricanes (Bian, 2017; Gehlot et al., 2018; Chapter 7), no work to our knowledge has employed joint choice modeling methods for wildfire behavior. Moreover, most public agencies lack the empirical knowledge of how individuals behave in wildfire evacuations, which could inform transportation response before, during, and after hazards. To address these two key literature gaps, we developed several research questions to guide our study:

1) What influences individuals to evacuate or stay/defend in a wildfire, particularly in a California context?
2) After deciding to evacuate, how do individuals make evacuation and logistical choices?
3) How are evacuation and logistical choices correlated and what influences these choices?

We answer these questions through the distribution of two surveys of individuals impacted by the 2017 December Southern California Wildfires (n=226) from March to July 2018 and the 2018 Carr Wildfire (n=284) from March to April 2019. In this paper, we first present a brief summary of evacuation behavior literature (predominately for hurricanes) followed by the current state of wildfire evacuation behavior literature, which has been less reviewed. Next, we present the methodology for developing two binary logit models, which capture the decision to evacuate or stay/defend, and two portfolio choice models (PCMs), which capture the multi-dimensional decision-making of evacuees without imposing a hierarchical or sequential structure. We discuss the modeling results and conclude with agency recommendations derived from the models.

Table 1: Major California Wildfires from 2017 to 2019 (Wong et al. 2020)

Wildfire	Location	Dates	Acres Burned	Structures Destroyed	Approx. Evacuees
Northern California Wildfires	Napa, Sonoma, Solano Counties	October 8, 2017 – October 31, 2017	144,987+	7,101+	100,000
Southern California Wildfires	Ventura, Santa Barbara, Los Angeles Counties	December 4, 2017 - December 15, 2017	303,983+	1,112+	286,000
Carr Fire	Shasta and Trinity Counties	July 23, 2018 – August 30, 2018	229,651	1,614	39,000
Mendocino Complex Fire	Mendocino, Lake, Glenn, and Colusa Counties	July 27, 2018 – September 19, 2018	459,123	280	17,000
Camp Fire	Butte County	November 8, 2018 – November 25, 2018	153,336	18,804	52,000
Woolsey Fire	Ventura and Los Angeles Counties	November 8, 2018 – November 21, 2018	96,949	1,643	250,000
Hill Fire	Ventura County	November 8, 2018 – November 16, 2018	4,531	4	17,000
Saddle Ridge Fire	Los Angeles County	October 10, 2019 – October 31, 2019	8,799	19	100,000
Kincade Fire	Sonoma County	October 23, 2019 – November 6, 2019	77,758	374	200,000
Tick Fire	Los Angeles County	October 24, 2019 – October 31, 2019	4,615	22	50,000
Getty Fire	Los Angeles County	October 28, 2019 – November 5, 2019	745	10	25,000

8.2) Literature

We first briefly review the literature on evacuation behavior with an emphasis on hurricanes, which has been the most studied hazard. We then present the current literature available on wildfire evacuation behavior.

8.2.1) Evacuation Behavior Research with Emphasis on Hurricanes

The evacuation behavior field stems from early work associated with impactful natural disasters such as the Big Thompson River Flood (Gruntfest, 1977), the partial meltdown of the Three Mile Island Nuclear Power Plant (Zeigler and Johnson, 1984; Cutter and Barnes, 1982; Stallings, 1984), and the eruption of Mt. St. Helens (Greene et al., 1981; Perry and Greene, 1983). Evacuations from floods and hurricanes have also been extensively studied through the collection of key descriptive statistics and the development of evacuee behavior frameworks (Drabek and Stephenson, 1971; Baker, 1979; Leik et al., 1981; Baker, 1990; Baker, 1991; Aguirre, 1991; Drabek, 1992; Dow and Cutter, 1998). Many of these hurricane evacuation studies expanded the state of knowledge through the exploration of the role of risk perceptions and communication in evacuee decision-making (Dow and Cutter, 2000; Dash and Morrow, 2000; Gladwin et al., 2001; Dow and Cutter, 2002; Lindell et al., 2005).

One primary development in the field has been the application of discrete choice models to determine the factors that impact different evacuation choices (Murray-Tuite and Wolshon, 2013). Discrete choice models are built on the assumption that individuals choose the alternative with the highest utility, or satisfaction. Ben-Akiva and Lerman (1985) provides an overview of discrete choice modeling and Wong et al. (2018) reviews research articles using discrete choice analysis for hurricane evacuations. Basic binary (two choice) and multinomial (multiple choice) logit models have been developed for the decision to evacuate or not (e.g., Whitehead et al., 2000; Zhang et al., 2004), destination choice (e.g., Cheng et al., 2011), shelter choice (e.g., Smith and McCarty, 2009; Deka and Carnegie, 2010), transportation mode choice (e.g., Deka and Carnegie, 2010), route choice (e.g., Akbarzadeh and Wilmot, 2015), and reentry compliance (e.g., Siebeneck et al., 2013). Recent advances in discrete choice modeling for transportation have also been applied in the evacuation field. For example, studies have constructed models for hurricane behavior including probit (based on a normal distribution), nested logit (allowing for a nesting and correlation of alternatives), and mixed logit (allowing for random parameters and capturing heterogeneity). Some examples of this hurricane behavior work include a nested logit model for mode choice (Sadri et al., 2014a) and shelter type (Mesa-Arango et al., 2013) and a mixed logit model for route choice (Sadri, 2014b).

Recently, research has attempted to model decision jointly, rather than in isolation. This shift in conceptualization focuses on the multi-dimensional choice that individuals and households may face. From the hurricane evacuation literature, Fu and Wilmot (2004) and Fu et al., (2006) developed a sequential logit model combining: 1) the decision to evacuation or stay and 2) departure timing. Following this work, Gudishala and Wilmot (2012) developed a time-dependent nested logit model to assess the interaction between the same two choices. Research has also been conducted jointly estimating transportation mode and destination type through a nested logit model (Bian, 2017) and estimating departure timing and travel times (a proxy for destination) through a joint discrete-continuous departure model (Gehlot et al., 2018). Finally, Chapter 7 of this dissertation developed a portfolio choice model (PCM) to jointly estimate departure day, departure time of day, destination, shelter type, transportation mode, and route, finding significant interactions among the choices. All of these studies found significant relationships and interactions between the modeled choices, indicating the need to continue exploring joint behavioral models, regardless of hazard type.

8.2.2) Wildfire Evacuation Behavior Research

In recent years, evacuations from wildfires have grown in both frequency and scope. With substantial development along the WUI, wildfires have become commonplace events in the US, particularly in western states such as California. In California alone, approximately 1.1 million people were ordered to evacuate in 2017 through 2019 from major wildfires (Wong et al., 2020). Yet, the research field on wildfire evacuations remains young, especially compared to evacuations for other hazards (e.g., hurricanes). Early work on wildfire evacuation behavior has focused largely on the decision to evacuate or stay (Fischer III et al., 1995; Benight et al., 2004). This has been more recently expanded to consider defending behavior, where some residents will try to protect their property (McCaffrey and Rhodes, 2009; Paveglio et al., 2010; McCaffrey and Winter, 2011;

Paveglio et al., 2014). Descriptive statistics have also been used to indicate how evacuees and non-evacuees respond to evacuation messaging and information (McCaffrey et al., 2013). In addition, several papers offer literature reviews on the community impacts of wildfires on WUI communities (Kumagai et al., 2004), the feasibility of a "stay and defend or leave early" (SDLE) approach in the US (McCaffrey and Rhodes, 2009), and the behavioral factors that impact wildfire decision-making (McLennan et al., 2014; McLennan et al., 2018). McLennan et al., (2018) offers an in-depth and systematic review of literature in the wildfire evacuation field, including studies across countries and employing both qualitative and quantitative methods.

To further understand wildfire evacuation behavior, some studies have employed discrete choice analysis, mostly for the decision to evacuate or stay/defend. Table 2 provides a description of each of these studies. More recent studies have begun to use revealed preference data from individuals recently impacted by wildfires (for example Toledo et al., 2018; McCaffrey et al., 2018; Lovreglio et al., 2019). Both Toledo et al. (2018) and Lovreglio et al. (2019) developed binary logit models to assess the factors that impacted the decision to evacuate or stay including demographics, mandatory evacuation orders, and risk perceptions. To extend the binary logit model to consider unobservable classes of individuals and model sample heterogeneity, McCaffrey et al., (2018) developed a latent class choice model (LCCM), finding distinct classes of evacuees based on wildfire risk perceptions and attitudes. Table 3 presents the significant factors found in these three studies on the decision to evacuate or stay/defend.

Table 2: Discrete Choice for Wildfire Evacuation Behavior

Authors (Year)	Wildfire(s)	Key Location(s)	Model Type	Wildfire Choice
Mozumder et al., (2008)	Hypothetical	East Mountain, Albuquerque, New Mexico	Binary Probit	Evacuate or Stay/Defend
Paveglio et al., (2014)	Hypothetical	Flathead County, Montana	Multinomial Logit	Evacuate or Stay/Defend
McNeill et al. (2015)	Hypothetical	Western Australia	Multinomial Logit	Evacuate or Stay/Defend + Delayed Response
Strahan (2017)	Perth Hills Bushfire (2014); Adelaide Hills Bushfire (2015)	Perth Hills, Australia; Adelaide Hills, Australia	Binary Logit	Evacuate or Stay/Defend
McCaffrey et al., (2018)	Various wildfires in the United States	Horry County, South Carolina; Chelan County, Washington; Montgomery County, Texas	Multinomial Logit + Latent Class	Evacuate or Stay/Defend
Toledo et al., (2018)	Haifa Wildfire (2016)	Haifa, Israel	Binary Logit	Evacuate or Stay/Defend
Lovreglio et al., 2019	Perth Hills Bushfire (2014); Adelaide Hills Bushfire (2015)	Perth Hills, Australia; Adelaide Hills, Australia	Binary Logit	Evacuate or Stay/Defend

Table 3: Key Factors for the Decision to Evacuate or Stay/Defend for Discrete Choice Models using Revealed Preference Data

Factors	Influence to Evacuate	Reference
Older Adult (55+)	+,(-)	Toledo et al. (2018); Lovreglio et al. (2019)
Young Adult (18-34)	+,-	Toledo et al. (2018); Lovreglio et al. (2019)
Gender (Female)	(+),(-)	Lovreglio et al. (2019); McCaffrey et al. (2018)
Children in Household	+,(-)	Toledo et al. (2018); Lovreglio et al. (2019)
Child (12 and under)	+	Toledo et al. (2018)
Household Size	+	Toledo et al. (2018)
Own Pets	-,(-)	Toledo et al. (2018); Lovreglio et al. (2019)
Low/Very Low-Income	-	Toledo et al. (2018)
High/Very High-Income	-	Toledo et al. (2018)
Evacuation Efficacy	+	McCaffrey et al. (2018); Lovreglio et al. (2019)
Staying/Defense Efficacy	-	McCaffrey et al. (2018); Lovreglio et al. (2019)
Self-Preparedness Level	(-),-	McCaffrey et al. (2018); Lovreglio et al. (2019)
Preparedness/Wildfire Knowledge	-,(+)	McCaffrey et al. (2018); Lovreglio et al. (2019)
Disaster Plan (Unwritten)	+	McCaffrey et al. (2018)
Family and/or Self Risk Perception	-,(-)	McCaffrey et al. (2018); Lovreglio et al. (2019)
General Risk Attitude	-	McCaffrey et al. (2018)
Fire Risk/Severity and Physical Cues	+/-	Toledo et al. (2018); McCaffrey et al. (2018)
Property Risk Perception	+	McCaffrey et al. (2018); Lovreglio et al. (2019)
Mandatory Evacuation Order	+	McCaffrey et al. (2018); Lovreglio et al. (2019)
Voluntary Evacuation Order	+	McCaffrey et al. (2018)
Limited Evacuation Routes	+	McCaffrey et al. (2018)
Official Cues	+	McCaffrey et al. (2018)

Note A: Parentheses indicate that the variable in that direction of influence was tested but was insignificant.
Note B: The multinomial logit model in McCaffrey et al. (2018) is presented as a comparison of "wait and see" and "stay and defend" to evacuating. Influence reflects the comparison of "stay and defend" against evacuating.

Some research in the wildfire evacuation field has collected qualitative data on evacuation behavior through interviews and focus groups (see Johnson et al., 2012 for a short overview). These studies have focused on the factors that influence preparedness (McGee and Russell, 2003), the impact of information and communication on evacuation decision (Taylor et al., 2005; Cohn et al., 2006; Stidham et al., 2011), and the role of social context and the impact of preparedness policies on evacuating or defending (Goodman and Proudley, 2008; Paveglio et al., 2010; McLennan et al., 2012; Cote and McGee, 2014; McCaffrey et al., 2015). We note that these studies cover a wide range of geographical areas (e.g., US, Australia, and Canada) and were conducted for either hypothetical wildfires or real wildfires.

A significant amount of research on wildfire evacuations has also focused on simulations that incorporate geographic information system (GIS) mapping techniques, traffic simulations, and fire spread models, beginning with early work by Cova and Johnson (2002). Other work identified evacuation trigger points – spatiotemporal points that indicate when and where an evacuation should be ordered – based on the characteristics of the wildfire (Cova et al., 2005). Much of this work in simulations has been expanded to consider buffer zones around these trigger points (Dennison et al., 2007; Larsen et al., 2011; Li et al., 2015), assessing clearance times from neighborhoods (Wolshon and Marchive, 2007), adding dynamics between fire spread and warnings into simulation methods (Beloglazvov et al., 2016), and leveraging machine learning in an experimental setting to simulate evacuee decision-making (Nguyen et al., 2018). In addition, simulations, both microscopic and mesoscopic, have been growing in the literature as a feasible mechanism to describe and predict traffic flows during wildfire evacuations (for framing, see Ronchi et al., 2017). A full review of traffic simulation models can be found in Intini et al. (2019), which also describes the need for improved modeling inputs through revealed preference behavior. Simulation research has also helped determine the effectiveness of different evacuation and transportation response strategies (Cova and Johnson, 2003; Chen and Zhan, 2008). From the perspective of the incident commander, work has been conducted on identifying which households should evacuate, shelter-in-place, or shelter-in-refuge (Cova et al., 2009; Cova et al., 2011).

Finally, wildfire evacuation research maintains a strong element of framework building and policy application. This has included lessons learned from previous evacuations of wildfires (Keeley et al., 2004; de Araujo et al., 2011; Woo et al., 2017) and frameworks built to consider the role of risk perception (MacGregor et al., 2007), communication (Mutch et al., 2011), and alternative evacuation strategies such as defending (Paveglio et al., 2012) on the evacuation decision making process. It should also be noted that a substantial amount of literature also covers pedestrian evacuation from fires in buildings (Kuligowski and Peacock, 2005; Ronchi and Nilsson, 2013; Kuligowski, 2013; Ronchi et al., 2014) with some examples using discrete choice analysis (Lovreglio et al., 2014; Lovreglio 2016). While this research topic is not directly related to our work on wildfire evacuations, we note it here as a potential source of inspiration for future work, especially if vehicular evacuations are rendered ineffective due to heavy congestion.

8.2.3) Key Gaps

Despite significant progress in understanding hurricane evacuation behavior, considerable gaps remain for wildfires. First, the lack of revealed preference studies using discrete choice on wildfire evacuation behavior limits any current conclusions on the consistency of factors that influence behavior. Moreover, little is known about wildfire evacuation behavior in a California context. Second, hurricane evacuation behavior modeling has indicated that evacuees likely make multiple evacuation decisions jointly. However, this remains unexplored in a wildfire evacuation case and it remains unclear if choices in wildfire evacuations are correlated. In this paper, we address these two gaps by: developing: 1) two binary logit models for the decision to evacuate or stay/defend; and 2) two portfolio choice models that allow for joint decision-making across choices. We develop these four models using revealed preference data from: 1) the 2017 December Southern California Wildfires from March to July 2018, and 2) the 2018 Carr Wildfire. Multiple datasets allow us to compare behavioral factors between two different fire contexts and geographies. We also contribute to the literature and practice by developing recommendations for improving evacuation outcomes using our modeling results and conclusions.

8.3) Methodology

With the context and key gaps established by the literature review, we next present the methodology, which includes descriptions of the survey data and discrete choice analysis.

8.3.1) Survey Data

The 2017 December Southern California Wildfires – composed primarily of the Thomas, Creek, Skirball, and Rye Fires – were a series of destructive wildfires predominately in Ventura, Santa Barbara, and Los Angeles Counties. Altogether, approximately 286,000 people were ordered to evacuate (Wong et al., 2020). Started in the early evening of December 4 near Thomas Aquinas College north of Santa Paula, the Thomas Fire was the largest of the wildfires, burning 281,893 acres and destroying 1,063 structures (Cal Fire, 2017a). The fire was caused by power lines owned by Southern California Edison, which slapped together in high winds and dropped molten material to the ground (Serna, 2019). Later in the early morning on December 5, the Creek Fire ignited near Little Tujunga Canyon and Kagel Canyon in Los Angeles County (Cal Fire, 2017b; St. John and Mejia, 2017). The fire impacted and threatened multiple neighborhoods in Los Angeles, including Sylmar, Lake View Terrace, Sunland-Tujunga, and Shadow Hills (Chandler, 2017). The cause of the fire is under investigation. The Rye Fire broke out later on December 5 in Santa Clarita in Los Angeles County (Los Angeles County Fire Department, 2018), while the Skirball Fire started along Interstate 405 near Bel-Air in Los Angeles on December 6 (Los Angeles County Fire Department, 2017). The Skirball Fire was started by an illegal cooking fire (Los Angeles County Fire Department, 2017), while the Rye Fire remains under investigation.

The 2018 Carr Wildfire was a large wildfire that started on July 23, 2018 by sparks from a vehicle with a flat tire (Agbonile, 2018; Cal Fire, 2018), severely impacting Shasta and Trinity Counties and the city of Redding, California. The fire led to the evacuation of 39,000 people (Wong et al., 2020), burned 229,651 acres, and destroyed 1,614 structures (Cal Fire, 2018). Extremely high winds, low humidity, and warm temperatures contributed to erratic fire behavior, which produced two observed fire whirls (NPS, 2018). The 2018 Carr Wildfire was contained after about one month after ignition (Agbonile, 2018).

We distributed an online survey to individuals impacted by: 1) the 2017 December Southern California Wildfires from March to July 2018, and 2) the 2018 Carr Wildfire from March to April 2019. The surveys asked respondents a range of questions related to their evacuation behavior along with their willingness to participate in the sharing economy in a future evacuation. Results from the sharing economy portion of the survey can be found in Wong and Shaheen (2019). To distribute the survey, we first compiled a list of local agencies, community-based organizations (CBOs), non-governmental organizations (NGOs), and news media in the same geographic region as each wildfire. Local agencies included transportation, transit, emergency management, social service, and health agencies. We also employed a snowball technique, allowing agencies to contact other agencies, news networks, and officials who might be interested in distributing the survey. All partnering agencies were allowed to post the survey to various online outlets including but not limited to Facebook, Twitter, agency websites, news websites, and alert subscription services. The goal of this wide distribution was to increase the coverage of the survey across the general population and increase the likelihood of reaching individuals unconnected to emergency management agencies. News websites were also leveraged to increase response rates and reduce self-selection bias.

We chose an online survey since it was a cost-effective and efficient method to gather responses quickly with a complex survey structure. To increase survey response and reduce self-selection bias, we also incentivized each survey through a drawing of gift cards. Participants in the 2017 Southern California Wildfire survey were offered the chance to win one of five $200 gift cards, while Carr Wildfire participants had the chance to win one of ten $250 gift cards. Once surveys were collected, responses were thoroughly cleaned to prepare the data for behavioral modeling. We note that discrete choice analysis requires highly cleaned data with mostly complete responses and demographic information. Due to the length of the survey (over 200 questions), we received responses that were not complete. Surveys that failed to answer the key choice questions (e.g., decision to evacuate or stay, departure time, destination, etc.) or important demographic characteristics (e.g., gender, age) were discarded from the final dataset. Table 3 presents a summary of each survey. Table A1 in the Appendix provides the demographic characteristics of survey responses and Tables A2, A3, and A4 present key choice responses.

Table 3: California Wildfire Surveys

	2017 Southern California Wildfires	2018 Carr Wildfire
Survey Timeline	March to July 2018	March to April 2019
Targeted Counties	Ventura, Santa Barbara, Los Angeles	Shasta, Trinity
Targeted Fires	Thomas, Creek, Skirball Fires	Carr Fire
Incentive	Drawing of five $200 gift cards	Drawing of ten $250 gift cards
Responses	552	647
Finished Responses	303	338
Finish Rate	55%	52%
Cleaned Sample	226	284
Distribution Method	Online via transportation agencies, emergency management agencies, community-based organizations, non-governmental organizations, and local media	

8.3.2) Discrete Choice Analysis

Discrete choice analysis (DCA) is a modeling technique to determine how a series of independent variables (characteristics of the decision-maker or alternatives) quantitatively influence the outcome that is modeled as a dependent variable (a decision-maker's choice). We assume that an individual behaves rationally by choosing an alternative that will maximize their utility – or satisfaction. Utility maximization assumes commensurability of attributes, and as such, an individual will make tradeoffs between independent variables to maximize this utility. We note here that utility maximization has been the primary decision rule in DCA (even though other decision rules such as regret minimization also exist). Discrete choice models that assume utility maximization have statistical properties that produce relatively simple, accurate, and tractable solutions (Ben-Akiva and Lerman, 1985; Washington et al., 2010). For this analysis, we also follow previous work in the field that uses probabilistic mechanisms, rather than solve the problem deterministically (see Ben-Akiva and Lerman, 1985 and Train, 2009 for overviews of the field and additional methodology). More recent work has continued to expand the field by developing: 1) latent class models to better capture lifestyle preferences (Walker, 2001), 2) simulations to estimate intractable models (Train, 2009) and 3) alternative decision rules, such as regret minimization, to explain behavior in different situations (Chorus et al., 2008). Of these new methods, latent class choice models have been successfully applied in an evacuation context for wildfires (McCaffrey et al., 2018), tsunamis (Urata and Pel, 2018), and hurricanes (Chapter 7). Regret minimization has also been applied in hypothetical disasters (An et al., 2015; Wang et al., 2017) and using post-disaster data in a revealed preference setting (Chapter 9).

For this research, we focus our attention on developing a traditional binary logit model for the decision to evacuate or stay/defend and a portfolio choice model (PCM) for multi-dimension evacuation choice. Both of these models employ the aforementioned random utility maximization methodology. For both models, we follow the procedures in Ben-Akiva and Lerman (1985), particularly in the selection of independent variables. We retain variables that were significant (or mostly significant), behaviorally important, and/or have a correct *a priori* coefficient sign. In some cases, we include a behaviorally important variable (based on past literature), even if the variable is not statistically significant to a 95% confidence level. We note that we prefer to present models with more inefficiency by including more variables, rather than models with higher bias from the exclusion of impacting variables. For the decision to evacuate or stay/defend, we also tested several mixed logit specifications and latent class choice model specifications. We found that both specifications failed to provide any additional behavioral insights for agencies due to insignificance in most tested variables. Future work should continue to test these model specifications using data from other wildfires.

For the PCM, we follow methodology developed in tourism choice behavior to reframe choice alternatives as a bundle of choice dimensions. The bundling of choices (as seen in Dellaert et al., 1997; Grigolon et al., 2012; Van Cranenburgh et al., 2014a; Van Cranenburgh et al., 2014b) permits the estimation of choice dimension dependency (which may or may not exist). The PCM also does not set any hierarchical or sequential requirements, increasing the flexibility of the model. We note that this does not mean that choices are not behaviorally hierarchical or sequential. To test these structures, further exploration of dependencies between choice dimensions should be explored via nested logit and sequential logit models. The purpose of the PCM is to identify any joint preferences that exist between choices by interacting dimensions (e.g., destination with shelter type). For the portfolio choice development, we follow methodology in Van Cranenburgh et al., (2014a) and Chapter 7 of this dissertation. Chapter 7 describes the portfolio choice setup in detail for an evacuation setting, including the derivation of probabilities. We present an abbreviated version of the PCM setup here.

To develop our portfolios, we first identify key evacuation choice dimensions that could be conceptualized as a bundle: departure day, departure time of day, destination, shelter type, transportation mode, and route as seen in Table 4 below.

Table 4: Consolidation of Choices for the Portfolio Choice Model

Choices Considered	*% of Evacuees (Southern California Wildfire)*	*% of Evacuees (Carr Wildfire)*	*Shorthand*
Sample Size (Evacuees Only)	***175***	***254***	
Departure Day			
Immediate Evacuees (Departed during the peak of wildfire threat)	61.1%*	78.3%**	Immediate
Non-Immediate Evacuees (Departed outside the peak time of wildfire threat)	38.9%	21.7%	Non-Immediate
Departure Timing by Hour			
Night (6:00 p.m. – 5:59 a.m.)	50.8%	72.5%	Night
Day (6:00 a.m. – 5:59 p.m.)	49.2%	27.5%	Day
Destination Choice			
Evacuated inside same county as residence	66.3%	66.1%	Within County
Evacuated to a different county	33.7%	33.9%	Out of County
Mode Choice			
Two or more personal vehicles	49.2%	61.8%	2+ Vehicles
One personal vehicle and all other modes	50.8%	38.2%	One Vehicle/Other
Shelter Type			
Private Shelter (Friends/Family/Other)	73.7%	84.2%	Private
Public Shelter (Public Shelter/Hotel/Motel)	26.3%	15.8%	Public
Primary Route by Road Type			
Highways	62.3%	38.2%	Highway
Major/Local/Rural/No Majority Type	37.7%	61.8%	Non-Highway

Total Portfolios: (2*2*2*2*2*2) = 64
Chosen Portfolios (Southern California Wildfires): 47
Chosen Portfolios (Carr Wildfire): 48
* December 4 and 5, 2017
** July 26, 2018

These dimensions are combined into a single bundle: individuals now chose one bundle of choices rather than a single choice. All bundles are now considered alternatives. The utility of each alternatives is linear-additive (identical to RUM models) and is composed of the utility of a dimension (e.g., stay at a public shelter) plus additional utilities associated with interactions between different dimensions (e.g., joint preference of staying at a public shelter and traveling to a within county destination). Socio-demographic variables (and their associated utility) may also be added for each primary dimension. We assume i.d.d. EV Type I error (as is common in the PCM literature), leading to closed form logit probabilities. Consequently, we can estimate the PCM through a standard multinomial model structure. We estimate the PCM using a maximum likelihood estimator through the Python package *Pylogit* (Brathwaite and Walker, 2018). We also note that the number of portfolios may be changed and could be increased indefinitely. However, more portfolios could give a false sense of precision when considering possible measurement errors in the data. After pre-testing, we split each dimension into a suitable number of categories to offer a rich overview of behavior that is policy applicable. In our case, we split each choice into a binary decision (see Table 4) due to the lower sample size of our datasets. We also note that there is no requirement for a portfolio to be chosen for the model to be estimable. As noted in Chapter 7, choice dimensions in a PCM are analogous to attributes (e.g. time and cost) of alternatives (e.g. mode) in a conventional RUM model. Parameters for these attributes can still be estimated even if a choice for a particular combination of attributes is unavailable in the dataset. Finally, we separate both the binary logit models and PCMs between the 2017 Southern California Wildfires and the 2018 Carr Wildfire, as combining datasets may lead to bias and model variables may not be transferable. However, future work should consider combining datasets in a similar way as Hasan et al. (2012) to test for transferability.

8.3.3) Research Limitations

While this study makes key contributions in evacuation behavior literature, we acknowledge that the research has several limitations. First related to our data, we note that our datasets contain some self-selection bias as individuals opted into the survey. The surveys were distributed to a wide population through different online platforms by multiple local agencies, non-governmental organizations, community-based organizations, and newspapers, but there is a strong likelihood that the survey was unable to reach some individuals. Specifically, those without access to the Internet or experience filling out online surveys were unable to participate in the study. We note as another limitation that the 2017 December Southern California Wildfires dataset was heavily skewed toward the Thomas Fire. Future research on wildfires (and other hazards) should continue to advance survey methodology to collect more representative samples of impacted individuals.

Related to our methodology, we acknowledge that we do not distinguish between evacuees who defended their property and evacuees who did not evacuate and did not defend. This distinction could be important, as the factors that influence these differing behaviors could be drastic. We were unable to model the distinction since our survey question only asked if an individual evacuated or not. Another key limitation is our usage of a binary logit choice model to understand evacuee behavior. While more advanced models account for sample heterogeneity (i.e., mixed logit, latent class), we found that these models did not provide any additional behavioral understanding that could be used by agencies after testing. We recognize that future work with these datasets (and other wildfire datasets) should continue to test other discrete choice models to better assess and predict evacuation behavior.

For our PCM methodology, we recognize that our division of categories for analysis into simple binary dimensions may obscure unique and alternative-specific behaviors. This limitation is largely a result of smaller sample sizes, as our construction of portfolios should not highlight levels of granularity that likely exceed measurement error in our data. We also note that several key choice dimensions, such as mobilization time, were not included in the PCMs since we did not ask individuals in our survey about the time it took for them to mobilize. We also note that the full PCMs with demographic variables contain many variables. Since additional demographic variables were somewhat or highly significant, we retained these variables to decrease model bias (opting instead for decreased efficiency). We also found that the demographic variables did substantially increase model fit, which further suggests that their inclusion is necessary.

8.4) Evacuate or Stay Model Results

We next present results from two binary logit models for the decision to evacuate or stay/defend in Table 5, which shows some similarities in key variables for both wildfires.

8.4.1) 2017 Southern California Wildfires Results

We found that individuals impacted by the 2017 Southern California Wildfires were more likely to evacuate if they received a mandatory evacuation order. This is consistent with work in McCaffrey et al. (2018), and Lovreglio et al. (2019). However, we found little difference in the specific fire (denoted by the Thomas Fire variable). For concerns and worry, extreme worry of the speed of the fire, extreme likelihood belief of utility loss, and extreme and somewhat likelihood belief of injury or death all increased the likelihood to evacuate. While fire speed and possible physical harm denote risk aversion to the fire, utility loss indicates concerns over livability, even if the individual wanted to defend their home from the fire. Without utilities, individuals might also be unable to receive evacuation orders and would have to prepare to evacuate without light (especially at night). Similar to our finding on fire speed, Toledo et al. (2018) found that higher fire risk and severity increased evacuations.

Extreme likelihood belief of structural damage and extreme and somewhat likelihood belief of work requirements decreased evacuating behavior. The concerns over structural damage is likely linked to defending behavior as an individual would want to protect their home from as much damage as possible, which is similar to results in McCaffrey et al. (2018). Work requirements, particularly for hourly jobs, encourages individuals to stay to avoid losing pay or being fired. Extreme and somewhat likelihood belief that first responders would not be available decreased probability of evacuating, but this was insignificant.

Table 5: Evacuate or Stay/Defend Modeling Results

	2017 Southern California Wildfires				2018 Carr Wildfire			
Variable	**Est. Coef.**	**Std. Error**	**p-value**		**Est. Coef.**	**Std. Error**	**p-value**	
Constant Evacuate	0.29	0.96	0.758		2.92	1.28	0.022	*
Evacuation Characteristics								
Received Mandatory Evacuation Order	2.14	0.49	<0.001	***	2.57	0.55	<0.001	***
Impacted by Thomas Fire	-0.20	0.65	0.757		------	------	------	
Concerns and Worry								
Extreme Worry of Speed of Fire	1.02	0.48	0.033	*	------	------	------	
Extreme or Somewhat Worry of Evacuation Housing Cost	------	------	------		-1.46	1.06	0.165	
Extreme Likelihood Belief of Utility Loss	1.65	0.55	0.003	**	0.49	0.52	0.353	
Extreme Likelihood Belief of Structural Damage	-1.27	0.63	0.044	*	1.28	0.65	0.050	*

Extreme and Somewhat Likelihood Belief of Work Requirements	-1.13	0.46	0.015	*	0.69	0.68	0.314	
Extreme and Somewhat Likelihood Belief of Injury or Death	1.53	0.65	0.019	*	------	------	------	
Extreme and Somewhat Likelihood Belief that First Respondents Would Not be Available	-0.83	0.50	0.098		------	------	------	
Household Characteristics								
Pets Present in Household	-0.61	0.48	0.208		-0.54	0.69	0.431	
Homeowner	-0.51	0.53	0.330		-0.66	0.76	0.388	
Very Low-Income (Annual Household Income Below $25,000)	-1.21	1.01	0.234		-1.93	0.78	0.013	*
Children Present in the Household	2.06	0.67	0.002	**	------	------	------	
Residing in the County for More than 10 Years	-0.96	0.51	0.058		------	------	------	
Individual Characteristics								
Female	0.54	0.48	0.262		0.50	0.48	0.294	
Previous Evacuee	-0.71	0.49	0.146		-1.55	0.66	0.020	*
Older Adult (65 and older)	0.81	0.63	0.197		------	------	------	
Young Adult (under 35)	------	------	------		1.84	0.95	0.052	
Higher Level Degree (Master's, Professional, Doctorate)	1.61	0.53	0.002	**	-----	------	-------	
Frequent Experience with Wildfire (3 or More Wildfires)	------	------	------		-1.66	0.54	0.002	**
Number of Observations	226				284			
Fit	0.52				0.68			
Adjusted Fit	0.41				0.61			
Final Log-Likelihood	-74.7				-63.1			
Initial Log-Likelihood	-156.7				-196.9			

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

For household characteristics, we found that individuals with pets, homeowners, and very low-income individuals (household income under $25,000) were all less likely to evacuate but the values were insignificant. We retained these variables due to the correct coefficient direction. Similar results for pet owners and low-income households were found in Toledo et al. (2018). Families were much more likely to evacuate due to their desire to protect their children from the fire (and likely smoke). Toledo et al. (2018) found similar results, while Lovreglio et al. (2019) found minimal impact. Long-term residents (residing in the county for more than ten years) were less likely to evacuate (although insignificant). For individual characteristics, we found that females and older adults (65 and older) were more likely to evacuate, and previous evacuees were less likely to evacuate (albeit insignificant). Lovreglio et al. (2019) also found that females were more likely to evacuate, though males were less likely to stay according to McCaffrey et al. (2018). Finally, we found that those with higher level degrees (i.e., Master’s, Professional, Doctorate) were more likely to evacuate. This might because these individuals have greater access to information, transportation, and sheltering resources that make evacuations easier.

We note that over half of identified people killed from the 2017 Northern California Wildfires (The Press Democrat, 2017) and the Camp Fire in 2018 (Newberry, 2019) were over the age of 65. In many of these cases, older adults did not have the transportation and mobility resources to be able to evacuate. The differences in modeling results and these facts may be due to several reasons that highlight some limitations of the work. First, any survey of disasters will not capture decision-making from individuals who were killed. Second, resources available to older adults differs by geographic location, which can be difficult to determine in just several surveys. Third, the 2017 Southern California Wildfires spread less rapidly than either the 2017 Northern California Wildfires or the 2018 Camp Fire. This temporal aspect, which could have provided even several more minutes to older adults, may have strongly impacted likelihood to evacuate. Finally, the management of evacuations likely influences evacuating behavior. In the 2017 Southern California Wildfires, officials were better able to notify individuals to evacuate and were more successful in managing congestion than in other major evacuations (Wong et al., 2020).

8.4.2) 2018 Carr Wildfire Results

We found that individuals impacted by the 2018 Carr Wildfire in Redding were more likely to prefer to evacuate (significant constant value) and were highly influenced by a mandatory evacuation order to leave (similar to McCaffrey et al., 2018, and Lovreglio et al., 2019). Mandatory evacuation orders are a powerful tool to convince individuals to evacuate and can also contain additional information regarding shelters, routes, destinations, and efforts that help others evacuate. For concerns and worry, we found only one significant variable, extreme likelihood belief of structural damage, which increased likelihood to evacuate. This result runs against the model for the 2017 Southern California Wildfires, but does show similarity with results from Lovreglio et al. (2018). While the reason for the difference is not readily clear, individuals impacted by the Carr Fire may equate structural damage with the severity of the disaster of the speed of the fire. Both these variables – severity and speed – were found to be insignificant in the Carr Wildfire model. Individuals with extreme or somewhat worry of evacuation housing costs were less likely to evacuate but the variable was insignificant. Utility loss was positive (same direction as the 2017 Southern California Wildfires) but was also insignificant. However, extreme and somewhat likelihood belief of work requirements was found to be positive (albeit insignificant), which runs counter to the 2017 Southern California Wildfires model.

For household characteristics, we found that individuals with pets and homeowners were less likely to evacuate, but the variables were insignificant. We did find that very low-income households were much less likely to evacuate (significant), which is likely a result of resource constraints and evacuation costs. This result was similar to the Southern California Wildfires and Toledo et al. (2018). Both children in the present in the household and long-term residence were insignificant and not included in the model. For individual characteristics, females and young adults were more likely to evacuate (insignificant). Toledo et al. (2018) found that both young adults and older adults were more likely to evacuate, when compared to middle-aged adults. However, Lovreglio et al. (2019) found that young adults (under 25) were less likely to evacuate. Previous evacuees were much less likely to evacuate, and poor past experiences likely played a role in this result. Similarly, those with significant wildfire experience (i.e., experiencing three or more wildfires) were more likely to stay. These individuals may have a greater knowledge of how to defend their property from fires and may view themselves as resilient to fires due to past experience.

8.5) Portfolio Choice Model (PCM) Results

We next present results of two portfolio choice models for the 2017 Southern California Wildfires and the 2018 Carr Fire. We provide a model with primary dimensions and interactions and a second model including demographic characteristics. We note that the inclusion of demographic variables moves some interaction variables to become less significant, indicating some explanatory power in demographics. As noted in the methodology, we retained variables that were behavioral consistent, had the correct a priori sign, and/or were statistically significant. We limited demographic variables to p-values under 0.2, indicating at least some significance. As noted in Chapter 7, the number of parameters in each portfolio model is not a major concern since a number of demographic variables were significant, added explanatory power that shifted primary dimensions and interactions, and did not significantly impact adjusted fit (which penalizes the inclusion of extra variables). As a limitation, we did not ask respondents about the situational conditions of the hazard, their mobilization time, or their social networks. Future surveys on evacuation behavior should consider capturing these variables. We also note that the PCM does not provide us with substantial detail of each interaction. Rather, the PCM helps identify correlated dimensions, which can be explored in further detail with other joint models or interacted via more granular categories that are policy relevant.

8.5.1) 2017 Southern California Wildfires - PCM Results

In Table 6 for primary dimensions and interactions, we found that individuals were more likely to evacuate during the day than at night. Individuals also preferred using highways over other road types. For interactions, we found a joint preference for immediate evacuations and nighttime evacuations, which highlights the wildfire circumstances in Southern California; the majority of evacuations at the height of the Thomas and Creek fires occurred at night. We also found a joint preference for immediate evacuations and private shelters. This result suggests that in the rapid breakout of the fire, people either preferred to stay with friends/family or they were unable to find shelter at public shelters or hotels. Individuals had a joint dislike for immediate and highway evacuations, likely because evacuees were first attempting to leave their neighborhoods quickly and not travel long distances. Indeed, we also found significant joint preference for nighttime evacuations and within county evacuations. This indicates that evacuees may have only wanted to travel to safety, not to a destination far away, to decrease risks of driving at night. We also found several insignificant interactions that will require additional study using other datasets. Interactions include: 1) a joint preference for within county and private shelter, 2) a joint dislike for within county and highway, and 3) a joint dislike for multiple vehicles and highway.

Table 6: Southern California Wildfire Portfolio Choice Model Results

	Primary + Interactions			Primary + Interactions + Demographics		
Variable	**Est. Coef.**	**Std. Error**	**p-value**	**Est. Coef.**	**Std. Error**	**p-value**

Immediate (Departed during the peak of wildfire threat)	-0.30	0.43	0.492		0.08	0.81	0.922	
Night (6:00 p.m. – 5:59 a.m.)	-1.28	0.35	<0.001	***	-3.21	0.75	<0.001	***
Within County (Same county as residence)	0.35	0.57	0.534		3.01	1.25	0.016	*
Private (Friends, family, or other)	-0.08	0.32	0.790		-0.69	0.55	0.214	
2+ Vehicles (Two or more personal vehicles)	0.11	0.25	0.644		-2.45	0.88	0.005	**
Highway (Over 50% of trip on highway)	1.94	0.54	<0.001	***	1.69	0.63	0.007	**
Immediate x Night	1.22	0.31	<0.001	***	1.31	0.33	<0.001	***
Immediate x Private	0.98	0.37	0.008	**	1.07	0.39	0.006	**
Immediate x Highway	-0.87	0.36	0.017	*	-0.58	0.38	0.120	
Night x Within County	1.12	0.35	0.001	***	1.28	0.37	0.001	***
Within County x Private	0.58	0.38	0.120		0.82	0.40	0.041	*
Within County x Highway	-0.99	0.52	0.057		-0.85	0.52	0.104	
2+ Vehicles x Highway	-0.40	0.32	0.214		-0.19	0.34	0.584	
Immediate								
Older Adult (65 and older)	-----	-----	-------		-0.94	0.42	0.025	*
Previous Evacuee	-----	-----	-------		0.83	0.36	0.021	*
Homeowner	-----	-----	-------		0.83	0.37	0.023	*
Impacted by Thomas Fire	-----	-----	-------		-1.70	0.69	0.014	*
Night								
Received Voluntary Order	-----	-----	-------		-1.24	0.36	0.001	***
Extreme Likelihood Belief of Structural Damage	-----	-----	-------		1.64	0.40	<0.001	***
Impacted by Thomas Fire	-----	-----	-------		2.23	0.59	<0.001	***
Within County								
Extreme Worry of Traffic	-----	-----	-------		-0.79	0.44	0.074	
Higher Level Degree (Master's, Professional, Doctorate)	-----	-----	-------		-0.63	0.39	0.101	
Children Present in Household	-----	-----	-------		-0.75	0.40	0.064	
Individual with Disability Present in Household	-----	-----	-------		-0.88	0.53	0.098	
Living in Residence for More than 10 Years	-----	-----	-------		1.38	0.41	0.001	***
Taking 5 or More Trips Prior to Evacuating	-----	-----	-------		1.29	0.75	0.084	
Impacted by Thomas Fire	-----	-----	-------		-2.97	1.09	0.007	**
Private Shelter								
Received Voluntary Order	-----	-----	-------		0.66	0.39	0.095	
Extreme Likelihood Belief of Injury or Death	-----	-----	-------		2.22	0.86	0.010	**
Extreme Likelihood Belief of Structural Damage	-----	-----	-------		-0.76	0.43	0.078	
Extreme Likelihood Belief of Work Requirements	-----	-----	-------		-1.45	0.48	0.002	**
Older Adult (65 and older)	-----	-----	-------		-0.66	0.46	0.144	

Female	-----	-----	-------	0.63	0.43	0.144	
Disabled	-----	-----	-------	1.02	0.64	0.113	
2+ Vehicles							
Received Mandatory Order	-----	-----	-------	0.95	0.40	0.018	*
Extreme Worry of Severity of Fire	-----	-----	-------	-0.69	0.37	0.066	
Pet in the Household	-----	-----	-------	0.76	0.37	0.039	*
Low-Income (Annual Household Income Below $50,000)	-----	-----	-------	-0.94	0.64	0.143	
Previously Experienced Wildfire	-----	-----	-------	0.91	0.66	0.163	
Own Two or More Vehicles	-----	-----	-------	1.51	0.38	<0.001	***
Highway							
Received Mandatory Order	-----	-----	-------	-0.99	0.42	0.018	*
Received Voluntary Order	-----	-----	-------	1.13	0.35	0.001	***
Number of Observations	175			175			
Parameters	13			42			
Fit	0.07			0.21			
Adjusted Fit	0.05			0.15			
Final Log-Likelihood	-626.5			-532.2			
Initial Log-Likelihood	-673.8			-673.8			

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

For immediate evacuations, we found that older adults were less likely to evacuate during the height of the wildfires. This could be a mobilization and/or resource challenge, which prevented these individuals from leaving quickly. Previous evacuees and homeowners were more likely to evacuate during the primary fire outbreak. Since the immediate evacuation variable was spread out over multiple days, we were unable to determine if homeowners defended their property up until the fire reached them. Future work in the wildfire behavior field should consider the time gap between evacuation and fire impact based on post-disaster surveys and fire spread models. Finally, we found that individuals impacted by the Thomas Fire were less likely to evacuate immediately. This likely reflects that Santa Barbara County and rural Ventura County were not affected by the Thomas Fire or related evacuations until several days after the immediate outbreak.

We found that individuals who received a voluntary evacuation order were less likely to evacuate at night (a likely function of increased risks evacuating at night, such as low visibility). Interestingly, however, those with an extreme likelihood of belief in structural damage to their property were more likely to evacuate at night. This may be related to perceived fire danger (i.e., fire may appear closer and more severe at night) and the unknown speed of the fire at night. Finally, individuals impacted by the Thomas Fire were more likely to evacuate at night, which aligns with the timeline of the fire and the dissemination of evacuation orders in the evening (Wong et al., 2020c).

In the case of within county evacuations, we only found two significant demographic variables. Those living in their residence for more than 10 years were more likely to stay within county, perhaps due to the stronger social connections they had in the area. Those impacted by the Thomas

Fire were more likely to leave the county, which corroborates evidence of travel patterns toward Los Angeles County in the data. Other variables were insignificant to the 95% confidence level including extreme worry about traffic, a higher-level degree (e.g., master's professional, doctorate), a household with children and individual(s) with disabilities, and individuals who took five or more trips to gather supplies or family members. These variables require further assessment in future surveys and PCMs.

For sheltering, we found that individuals who strongly believed they would have work requirements (e.g., required to work during the evacuation or recovery period) were less likely to stay at private shelters. Further, public shelters and local hotels/motels may have been in closer proximity, giving workers easy access to return to work (and avoid being fired for not showing up). Individuals with an extreme likelihood belief of injury/death due to the wildfire were also more likely to stay at private shelters, perhaps opting to be close to their social networks. Other variables that were insignificant and should be tested in future work include: risk perception of structural damage, gender (female), individuals with disabilities, and older adults.

Individuals who received a mandatory evacuation order were more likely to evacuate with two or more vehicles. These individuals were likely motivated to protect their personal vehicles. Households with pets were more likely to use multiple vehicles, which is possibly related to a need for extra space. One unsurprising result was that households that owned two or more vehicles were more likely to take multiple vehicles, likely due to vehicle availability and wanting to protect them. Further research is needed to look at non-significant variables including risks perceptions related to fire speed, lower-income households, and those with previous wildfire experience.

For route choice, we found only evacuation orders to be influential. Those who received a mandatory evacuation order were less likely to take highways. However, individuals who received a voluntary evacuation order were more likely to use a highway. The use of a highway in contrast to local roads may reflect their longer lead time to prepare for a long-distance trip.

8.5.2) 2018 Carr Wildfire – PCM Results

In Table 7 for the primary dimension and interactions model, we found that none of the primary dimensions for the 2018 Carr Wildfire PCM were significant, indicating no substantial preferences in those dimensions. However, we found a joint preference for night and within county evacuations, indicating a desire to remain closer to home during a higher risk time period with lower visibility (i.e., nighttime). We also found a joint preference of within county evacuations and private shelters, suggesting strong social networks in the Redding area within Shasta County. We also found a joint dislike for within county and highway evacuations, which reflects just a single highway in Shasta County (Interstate 5). With shorter distance trips, arterial and local roads were preferred. When demographic variables were added, we found that individuals do not prefer two or more vehicles. This is due to the strength of several demographics that positively influence using multiple vehicles. We also found a shift in interactions with a joint preference in night and multiple vehicle evacuations. While an explanation for this preference is not readily apparent, the preference is likely a result of the evacuation circumstances in the Redding area.

Table 7: Carr Fire Portfolio Choice Model Results

	Primary + Interactions				Primary + Interactions + Demographics			
Variable	**Est. Coef.**	**Std. Error**	**p-value**		**Est. Coef.**	**Std. Error**	**p-value**	
Immediate (Departed during the peak of wildfire threat)	0.21	0.34	0.526		0.25	0.50	0.612	
Night (6:00 p.m. – 5:59 a.m.)	-0.33	0.35	0.344		-0.51	0.62	0.411	
Within County (Same county as residence)	-0.50	0.52	0.337		-0.64	0.61	0.298	
Private (Friends, family, or other)	0.56	0.31	0.073		0.40	0.41	0.328	
2+ Vehicles (Two or more personal vehicles)	-0.71	0.47	0.131		-2.02	0.60	0.001	***
Highway (Over 50% of trip on highway)	0.25	0.23	0.268		-0.12	0.60	0.838	
Immediate x Night	0.53	0.34	0.112		0.85	0.36	0.018	*
Immediate x Within County	0.56	0.32	0.082		0.55	0.33	0.094	
Immediate x 2+ Vehicles	0.43	0.32	0.178		0.29	0.34	0.390	
Night x Within County	0.73	0.30	0.014	*	0.81	0.31	0.009	**
Night x 2+ Vehicles	0.47	0.30	0.110		0.65	0.31	0.036	*
Within County x Private	0.87	0.36	0.016	*	0.78	0.36	0.033	*
Within County x Highway	-1.22	0.29	<0.001	***	-1.23	0.29	<0.001	***
Private x 2+ Vehicles	0.62	0.35	0.079		0.66	0.36	0.069	
Immediate Departure								
Extreme Likelihood Belief of Injury or Death	-------	-------	--------		-1.41	0.50	0.005	**
Homeowner	-------	-------	--------		0.68	0.42	0.107	
Low-Income (Annual Household Income Below $50,000)	-------	-------	--------		-0.91	0.38	0.017	*
Living in Residence for More than 10 Years	-------	-------	--------		-0.66	0.36	0.067	
Nighttime								
Received Voluntary Order	-------	-------	--------		-0.78	0.35	0.024	*
Extreme Likelihood Belief of Injury or Death	-------	-------	--------		1.94	0.76	0.010	**
Extreme Likelihood Belief that First Respondents Would Not be Available	-------	-------	--------		-0.89	0.44	0.044	*
Higher Level Degree (Master's, Professional, Doctorate)	-------	-------	--------		0.62	0.32	0.053	
Previous Evacuee	-------	-------	--------		0.51	0.32	0.110	
Has a Disability	-------	-------	--------		-1.07	0.39	0.007	**
Homeowner	-------	-------	--------		-0.80	0.45	0.077	
Low-Income (Annual Household Income Below $50,000)	-------	-------	--------		1.38	0.47	0.003	**
County								
Extreme Likelihood Belief of Work Requirements	-------	-------	--------		0.60	0.38	0.115	

Higher Level Degree (Master's, Professional, Doctorate)	-------	-------	--------	-0.68	0.29	0.018	*
Pet in the Household	-------	-------	--------	0.56	0.34	0.092	
Private							
Extreme Worry of Speed of Fire	-------	-------	--------	0.70	0.40	0.079	
Extreme Worry of Finding Housing	-------	-------	--------	-1.31	0.53	0.013	*
Extreme Likelihood Belief of Work Requirements	-------	-------	--------	1.35	0.63	0.032	*
Older Adult (65 and older)	-------	-------	--------	1.13	0.55	0.038	*
Has a Disability	-------	-------	--------	-1.57	0.41	<0.001	***
2+ Vehicles							
Children Present in Household	-------	-------	--------	1.34	0.33	<0.001	***
Low-Income (Annual Household Income Below $50,000)	-------	-------	--------	-0.91	0.35	0.010	**
Extreme Likelihood Belief of Injury or Death	-------	-------	--------	1.02	0.30	0.001	***
Own Two or More Vehicles	-------	-------	--------	0.80	0.31	0.008	**
Highway							
Received Voluntary Order	-------	-------	--------	0.74	0.30	0.014	*
Extreme Likelihood Belief of Injury or Death	-------	-------	--------	0.73	0.48	0.129	
Homeowner	-------	-------	--------	-0.68	0.34	0.045	*
Previously Experienced Wildfire	-------	-------	--------	0.71	0.49	0.147	
Number of Observations	254			254			
Parameters	14			42			
Fit	0.14			0.21			
Adjusted Fit	0.12			0.17			
Final Log-Likelihood	-850.7			-775.1			
Initial Log-Likelihood	-983.3			-983.3			

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

For immediate departure variables, we found that those with an extreme likelihood belief in an injury or death due to the wildfire were less likely to depart at the height of the evacuation. This result might be influenced by the construction of the choice dimension (i.e., the height of the Carr Wildfire did not occur until several days following the initial breakout). Lower-income individuals were less likely to evacuate during the height of the fire, which may be due to a resource deficiency.

Individuals who received a voluntary evacuation order were less likely to evacuate at night, which parallels results from the Southern California Wildfire PCM. Individuals with a high risk perception (e.g., likelihood of injury/death) and lower-income households (i.e., under $50,000) were more likely to evacuate at night. The visual fire level at night could have influenced those with a high-risk perception. Among lower-income households, living in downtown Redding and further west in Shasta County, income-related results are likely tied to timing of evacuation orders. Individuals who did not think first responders would be available were less likely to evacuate at night, likely preferring to have guidance from police and fire before leaving. Individuals with disabilities were less likely to evacuate at night, perhaps due to more risks at night.

For response to evacuation destination, education level (i.e., higher education) was the only significant variable, corresponding to a lower likelihood to stay within county (similar to the Southern California Wildfire PCM) as they probably have additional income and/or connections outside the area to travel further distances. Non-significant variables that require additional analysis include a strong belief in work requirements (which constitutes the possibility of being fired for not showing up to work) and households with pets.

Those who believed they had work requirements were more likely to shelter with a friend or family member (running contrary to the Southern California Wildfire PCM). Older adults were also more likely to shelter with friends/family, which also runs counter to results from the Southern California Wildfire PCM. Geographical and cultural context may be impacting directionality for these variables. Those worried about finding housing were more likely to shelter at a hotel or a public shelter. Finally, those with a disability were less likely to shelter with friends/family, which may indicate poorer social networks or receiving assistance from a caretaker (but not a friend or family member).

For transportation mode, we found that households that have children and own two or more vehicles were more likely to take multiple vehicles. This result mirrors the Southern California Wildfire PCM results, particularly in relation to multiple vehicle ownership. Individuals with a higher risk perception related to injury/death were also more likely to take multiple vehicles, which differs somewhat from the Southern California Wildfire PCM results. Low-income households were less likely to take two or more vehicles, which highlights resource constraints.

We found for route choice that those who received a voluntary evacuation were more likely to use the highway (perhaps due to longer lead times), but homeowners were less likely to use highways (perhaps due to knowledge of arterial, local, and rural roads to evacuate). Several insignificant variables included: those with an extreme likelihood belief of injury/death and individuals with prior wildfire experience. Based on these results and the Southern California Wildfire PCM results, demographic variables are likely poor predictors of route choice.

8.6) Recommendations

To consolidate results and provide practice-ready strategies for practitioners, we present several recommendations for wildfire evacuations. These recommendations are largely based off the discrete choice results. We note that some of these recommendations are not novel or particularly innovative. However, they are provided to build more consensus on practice-ready strategies for improving evacuation outcomes. Additional recommendations for wildfire logistics management and building a shared resource evacuation strategy can be found in Wong and Shaheen (2019) and Chapter 4. We use the following abbreviations in the recommendations section: SoCal (2017 December Southern California Wildfires) and Carr (2018 Carr Wildfire).

8.6.1) Evacuation Orders

Recommendation: Agencies should focus on distributing mandatory evacuation order quickly and widely to increase evacuations. These orders could also contain additional information (e.g., shelters, safe routes) to increase situational awareness.

> Evidence: Modeling results indicate that individuals who receive a mandatory evacuation order are much more likely to evacuate.

Recommendation: Agencies should focus communication efforts in neighborhoods that have more low-income residents, homeowners, long-term residents, and previous evacuees. Additional transportation resources will be also be needed to assist very low-income residents (such as public transit), along with more sheltering options.

> Evidence: Modeling results indicate that very low-income residents (SoCal and Carr), homeowners (SoCal and Carr), previous evacuees (SoCal and Carr), and long-term residents (SoCal) were less likely to evacuate. Evacuees who were extremely or somewhat worried about evacuation housing costs were less likely to evacuate (Carr).

Recommendation: Agencies should prepare additional traffic measures, especially on-ground traffic control by personnel, for areas without power or areas likely to lose power to handle additional congestion. Low-tech communication mechanisms (e.g., radios, sirens) should also be considered to provide information on safe routes.

> Evidence: Modeling results indicate that those with an extreme likelihood belief of utility loss were more likely to evacuate (SoCal and Carr).

Recommendation: Agencies should inform residents about pet-friendly shelters and allow pets on public transportation during an evacuation to increase evacuation rates. Agencies may also need to coordinate with local animal shelters and community-based organizations (CBOs) to provide information or additional space for pets.

> Evidence: From the modeling results, individuals with pets were less likely to evacuate (SoCal and Carr).

8.6.2) Departure Timing

Recommendation: Agencies should prepare for significant localized congestion during nighttime evacuations at the height of the wildfires. Agencies should identify neighborhoods with only a single exit, where localized congestion is likely to occur. Personnel should be prepared to direct traffic, alter signal timing, and increase capacity (via contraflow and shoulder-running) to handle nighttime traffic.

> Evidence: Evacuees had a joint preference from the PCM for night-within county evacuations (both SoCal and Carr), night-immediate evacuations (both SoCal and Carr), and night-multiple vehicle evacuations (just Carr).

Recommendation: State transportation agencies should focus on deploying assets on arterial streets and two-lane state highways during the immediate outbreak of the wildfire before deploying resources on interstates or limited access highways. However, if fire threatens these assets, state agencies should continue to respond effectively with closures and assets when and where necessary.

> Evidence: For the SoCal PCM, individuals expressed a joint dislike for immediate-highway evacuations. Evacuees prefer to make short-distance trips at the height of the wildfires and often do not use highways for within county travel.

Recommendation: Local public transit agencies should have a plan to rapidly respond in a wildfire to effectively transport evacuees, especially older adults and low-income households. Public transit offers a free option for residents to evacuate, but only if vehicles and drivers are deployed quickly and to pre-identified locations that are publicly known.

> Evidence: Older adults (SoCal) and low-income households (Carr) were less likely to evacuate at the height of the wildfires at noted in the PCMs.

Recommendation: Agencies should be prepared for substantial evacuations for large wildfires at night and should us only mandatory evacuation orders to elicit nighttime evacuations. Agencies should be aware that voluntary evacuation orders are not effective in encouraging people to leave at night.

> Evidence: Risk perception variables (i.e., major structural damage, potential for injury/death) increased likelihood to evacuate at night, while voluntary evacuation orders decreased likelihood to evacuate at night.

8.6.3) Destination, Transportation Mode, and Route

Recommendation: Agencies should be prepared for significant traffic within counties (rather than multi-county traffic), including highly localized traffic into residential neighborhoods outside the impact and mandatory evacuation area.

> Evidence: From both the SoCal and Carr PCMs, evacuees jointly preferred private shelters and within county destinations, which indicates substantial sheltering with friends and family in nearby neighborhoods. In addition, approximately 66% of evacuees from both fires (SoCal and Carr) evacuated within county.

Recommendation: Agencies should prepare for additional congestion at night from multi-vehicle evacuations. Transportation responses will have to be feasible at night (i.e., signal changes), and personnel will have to be properly trained in low visibility circumstances.

> Evidence: From the Carr PCM, individuals exhibited a joint preference for nighttime and multi-vehicle evacuations.

Recommendation: Agencies should increase personnel and transportation response for congestion in neighborhoods with a high concentration of families, high vehicle ownership, and prior experience with wildfires. Agencies should also deploy congestion-reduction measures in mandatory evacuation areas prior to the communication of orders. Resources will also need to be available for lower-income neighborhoods to increase mandatory evacuation compliance and increase equitable outcomes. Community-based organizations could serve as a trusted authority within the community to provide resources.

Evidence: Families and multiple-vehicle owners were more likely to use multiple vehicles (SoCal and Carr PCMs). Individuals who received a mandatory evacuation order were more likely to use multiple vehicles (SoCal PCM), while those with prior experience with wildfires were somewhat more likely to use multiple vehicles (Carr PCM). Low-income households were less likely to evacuate (SoCal and Carr).

Recommendation: Agencies should increase local road congestion reduction measures near mandatory evacuation zones while increasing highway measures near voluntary evacuation zones.

Evidence: Evacuees who received a mandatory evacuation order were more likely to use local roads (SoCal), while evacuees who received a voluntary evacuation order were more likely to use highways (SoCal and Carr).

8.7) Conclusions

In this study, we present a comprehensive analysis of wildfire behavior using: 1) two binary logit models for the decision to evacuate or not; and 2) two portfolio choice models (PCMs) for multi-dimensional decision-making (e.g., departure day, departure time of day, destination, shelter type, transportation mode, and route). We constructed the four models using data collected from individuals who were impacted by the 2017 December Southern California Wildfires (n=226) and the 2018 Carr Wildfire (n=284).

First, we found similarities between our two wildfires in terms of factors influencing the decision to evacuate or not evacuate. Most clear was the impact of mandatory evacuation orders and risk perception (i.e., environmental cues) that increased willingness to evacuate. Demographic variables were less clear and were sometimes significant for one wildfire but insignificant for the other wildfire (i.e., homeownership, age, education, length of resident). However, we did find that previous evacuees and very low-income households were less likely to evacuate for both wildfires, suggesting stronger influence and more conclusive results.

Second, we determined that a significant number of evacuation choice dimensions (after the decision to evacuate) exhibit clear dependency and joint behavior. However, the joint behavior was rarely the same between wildfires, suggesting that wildfires exhibiting different characteristics (e.g., speed, severity) and impacting different geographies (e.g., populations and demographics) likely lead to different choices. Consequently, wildfire evacuation behavior may be highly dependent on context and geography, which diminishes transferability of wildfire evacuation strategies. Preparedness and response strategies may need to be highly tailored to each jurisdiction for multiple wildfire scenarios.

While a considerable amount of future work will be necessary, this study serves as a stepping stone for wildfire evacuation behavior research and offers a suite of recommendations for agencies to begin developing effective preparedness, response, and recovery plans for wildfires.

8.8) Acknowledgements

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8.9) Appendix

Table A1: Demographic Characteristics of Survey Respondents

	2017 Southern California Wildfires	**2018 Carr Wildfire**
Sample Size (All Respondents)	*n=226*	*n=284*
Individual Characteristics		
Gender		
Male	26.1%	30.3%
Female	73.9%	69.7%
Age		
18-24	2.7%	2.8%
25-34	17.7%	12.7%
35-44	15.0%	19.0%
45-54	19.0%	22.9%
55-64	26.5%	19.7%
65+	19.0%	22.9%
Race		
Asian	2.7%	1.1%
Black or African American	0.4%	0.0%
Mixed	7.5%	3.5%
Native American/Alaska Native	0.4%	1.4%
Pacific Islander	0.9%	0.0%
White	81.4%	90.8%
Other	4.0%	0.0%
Prefer not to answer	2.7%	3.2%
Ethnicity		
Hispanic	11.1%	5.3%
Not Hispanic	76.1%	87.3%
Prefer not to answer	12.8%	7.4%
Education		
No high school degree	0.0%	0.7%

High school graduate	0.9%	4.9%
Some college	15.9%	23.2%
2-year degree	5.8%	12.0%
4-year degree	41.2%	27.8%
Graduate or professional degree	28.3%	27.5%
Doctorate	8.0%	3.9%
Prefer not to answer	0.0%	0.0%
Employment		
Employed full time	57.1%	47.9%
Employed part time	11.9%	10.9%
Unemployed looking for work	2.2%	2.8%
Unemployed not looking for work	2.7%	4.2%
Retired	22.1%	26.1%
Student	2.2%	1.8%
Disabled	1.3%	2.8%
Prefer not to answer	0.4%	3.5%
Primary Mode of Transportation*		
Drive alone using a car, SUV, pickup, or van	87.6%	92.6%
Carpool/vanpool	2.2%	1.4%
Rail (e.g., light/heavy, subway/metro, trolley)	0.9%	0.0%
Bus	1.8%	0.0%
Motorcycle/scooter	0.9%	0.4%
Bicycle	0.9%	0.7%
Walk	0.4%	0.0%
Shuttle service	0.0%	0.4%
Work from home	1.8%	1.4%
Other	0.9%	2.8%
Prefer not to answer/No answer	2.7%	0.4%
Decision Making Role		
I am the sole decision-maker	25.2%	18.3%
I am the primary decision-maker with input from another household member	19.9%	19.4%
I share equally in making decisions with another household member(s)	51.3%	57.4%
I provide input into the decisions, but I am not the primary decision-maker	2.2%	3.2%
Another person is the sole decision-maker	0.4%	1.4%
Prefer not to answer	0.9%	0.4%
Previous Evacuee*		
Yes	35.3%	31.0%
No	64.7%	69.0%
Previous Wildfire Experience**		
Yes	93.4%	89.1%
No	6.6%	10.9%
Cell Phone Type		
Do not own a cell phone	2.7%	3.2%
Own a typical cell phone (non-smartphone)	5.3%	3.9%
Own a smartphone	92.0%	93.0%
Access to Internet at Home		
Yes	98.7%	97.2%

No	1.3%	2.8%
In-Vehicle or Smartphone Navigation* **		
Yes	79.6%	78.2%
No	20.4%	21.8%
Household Characteristics		
Displacement after Wildfire		
Same Residence	88.9%	87.0%
Displaced	10.6%	13.0%
No answer	0.4%	0.0%
Length of Residence†		
Less than 6 months	5.8%	3.2%
6 to 11 months	4.9%	5.3%
1 to 2 years	12.4%	13.7%
3 to 4 years	14.6%	9.5%
5 to 6 years	7.1%	7.7%
7 to 8 years	5.3%	5.3%
9 to 10 years	4.9%	6.0%
More than 10 years	45.1%	49.3%
Residence Structure†		
Site build (single home)	73.9%	91.2%
Site build (apartment)	19.5%	4.2%
Mobile/manufactured home	6.2%	4.6%
Prefer not to answer	0.4%	0.0%
Homeownership†		
Yes	67.3%	81.3%
No	29.6%	17.3%
Prefer not to answer	3.1%	1.4%
Live in Cal Fire High Risk Area††		
Yes	38.1%	37.7%
No	28.8%	35.2%
I don't know	33.2%	27.1%
Household Characteristics		
Household with Disabled	14.2%	18.7%
Household with Children	25.2%	35.2%
Household with Elderly	28.3%	31.3%
Households with Pets	63.7%	81.7%
Household Income		
Less than $10,000	0.4%	0.7%
$10,000 - $14,999	1.3%	3.9%
$15,000 - $24,999	2.2%	2.8%
$25,000 - $34,999	2.2%	5.6%
$35,000 - $49,999	6.2%	9.5%
$50,000 - $74,999	14.6%	17.6%
$75,000 - $99,999	11.5%	14.8%
$100,000 - $149,999	21.2%	19.7%
$150,000 - $199,999	13.3%	5.6%
$200,000 or more	14.2%	8.1%

Prefer not to answer	12.8%	11.6%
County of Residence		
Ventura	43.8%	------
Santa Barbara	41.6%	------
Los Angeles	13.3%	------
Shasta	-------	94.0%
Other California	1.3%	2.5%
Non-California	0.0%	3.5%

* "How many times have you evacuated from any residence prior to this disaster?"
** "How many times have you experienced a wildfire?"
*** Under normal conditions
† At the time of the wildfire
†† At the time of the wildfire and very high or high fire severity zone as defined by the California Department of Forestry and Fire Protection

Table A2: Key Evacuation Choices of Survey Respondents

	2017 Southern California Wildfires	2018 Carr Wildfire
Sample Size (All Respondents)	*n=226*	*n=284*
Evacuation Choice		
Evacuated	77.4%	89.4%
Did Not Evacuate	22.6%	10.6%
Sample Size (Evacuees Only)	*n=175*	*n=254*
Departure Timing by Hour		
12:00 AM - 5:59 AM	23.4%	9.1%
6:00 AM - 11:59 AM	24.6%	7.9%
12:00 PM - 5:59 PM	24.6%	19.7%
6:00 PM - 11:59 PM	27.4%	63.4%
Shelter Type		
Friend's residence	30.3%	39.8%
Family member's residence	32.6%	29.9%
Hotel or motel	22.9%	13.4%
Public shelter	3.4%	2.4%
Second residence	2.9%	3.1%
Portable vehicle (e.g., camper, recreational vehicle [RV])	4.0%	5.1%
Peer-to-peer service (e.g., Airbnb)	1.1%	0.4%
Other	2.9%	5.9%
Primary Route by Road Type		
Highways	62.3%	38.2%
Major roads	15.4%	16.9%
Local roads	4.0%	4.7%
Rural roads	1.1%	4.7%
No majority type	17.1%	35.4%
Usage of GPS for Routing		
Yes, and followed route	18.3%	7.5%
Yes, but rarely followed route	4.6%	5.5%

No	77.1%	87.0%
Multiple Destinations		
Yes	41.7%	48.4%
No	58.3%	51.6%
Returned Home		
Yes	92.6%	96.9%
No	7.4%	3.1%
Within County Evacuation		
Yes	66.3%	66.1%
No	33.7%	33.9%
Mode Choice*		
One personal vehicle	45.1%	33.9%
Two personal vehicles	40.6%	45.3%
More than two personal vehicles	8.6%	16.5%
Aircraft	0.6%	0.0%
Rental car	0.6%	0.0%
RV	1.1%	2.4%
Truck and trailer	2.3%	0.0%
Non-household carpool	1.1%	1.2%
Carsharing	0.0%	0.4%
Walk	0.0%	0.4%

* Other transportation mode options asked in the survey but received no responses: bus; rail (e.g., light/heavy, subway/metro, trolley; shuttle service; motorcycle/scooter; bicycle; ridesourcing/TNC (e.g., Uber, Lyft)

Table A3: Bivariate Cross Tabulations for Evacuation Decision and Mandatory Order

2017 Southern California Wildfires *(n=226)*		**Evacuation Decision** Yes	No
Received Mandatory Evacuation Order	Yes	87.0%	**13.0%**
	No	**62.5%**	37.5%
	Total	77.4%	22.6%

2018 Carr Wildfire *(n=284)*		**Evacuation Decision** Yes	No
Received Mandatory Evacuation Order	Yes	96.8%	**3.2%**
	No	**75.0%**	25.0%
	Total	89.4%	10.6%

Table A4: Departure Day and Destination by County of Survey Respondents

2017 Southern California Wildfires		**2018 Carr Wildfire**	
n=175		n=254	
Departure Day			
Monday, Dec. 4	32.6%	Monday, July 23	2.4%
Tuesday, Dec. 5	28.6%	Tuesday, July 24	2.0%
Wednesday, Dec. 6	5.1%	Wednesday, July 25	8.3%

Thursday, Dec. 7	4.0%	Thursday, July 26	78.3%
Friday, Dec. 8	4.6%	Friday, July 27	5.9%
Saturday, Dec. 9	3.4%	Saturday, July 28	0.8%
Sunday, Dec. 10	8.0%	Sunday, July 29	0.0%
After Sunday, Dec. 10	13.7%	After Sunday, July 29	2.4%
Destination by County			
Ventura	37.1%	Shasta	66.5%
Santa Barbara	25.7%	Tehama	5.9%
Los Angeles	18.9%	Sacramento	4.7%
San Luis Obispo	5.7%	Siskiyou	3.1%
Monterey	2.9%	Butte	2.8%
All counties under 5 respondents each	9.7%	All counties under 5 respondents each	16.9%

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Chapter 9: A Revealed Preference Methodology to Evaluate Regret Minimization with Challenging Choice Sets: A Wildfire Evacuation Case Study

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ABSTRACT

Regret is often experienced for difficult, important, and accountable choices. Consequently, we hypothesize that random regret minimization (RRM) may better describe evacuation behavior than traditional random utility maximization (RUM). However, in many travel related contexts, such as evacuation departure timing, specifying choice sets can be challenging due to unknown attribute levels and near-endless alternatives, for example. This has implications especially for estimating RRM models, which calculates attribute-level regret via pairwise comparison of attributes across all alternatives in the set. While stated preference (SP) surveys solve such choice set problems, revealed preference (RP) surveys collect actual behavior and incorporate situational and personal constraints, which impact rare choice contexts (e.g., evacuations). Consequently, we designed an RP survey for RRM (and RUM) in an evacuation context, which we distributed from March to July 2018 to individuals impacted by the 2017 December Southern California Wildfires (n=226). While we hypothesized that RRM would outperform RUM for evacuation choices, this hypothesis was not supported by our data. We explain how this is partly the result of insufficient attribute-level variation across alternatives, which leads to difficulties in distinguishing non-linear regret from linear utility. We found weak regret aversion for some attributes, and we identified weak class-specific regret for route and mode choice through a mixed-decision rule latent class choice model, suggesting that RRM for evacuations may yet prove fruitful. We derive methodological implications beyond the present context toward other RP studies involving challenging choice sets and/or limited attribute variability.

Keywords: Evacuation Behavior, Regret Minimization, Revealed Preference, Discrete Choice Analysis, California Wildfires

9.1) Introduction

For major disasters in the United States (US), evacuations are the primary method to protect citizens. Recent disasters (e.g., wildfires in California in 2017 and 2018) demonstrate the immense challenges of coordinating, managing, and distributing transportation resources. Concurrently, individuals make multiple important evacuation decisions (i.e., evacuate or stay, departure time, destination, shelter type, transportation mode, reentry day), impacting transportation resource use. Most research has modeled evacuation behavior by assuming individuals maximize their utility, commonly specified as a linear function of attributes and associated parameters, which implies fully compensatory choice behavior. Yet, based on behavioral science literature, one may hypothesize that such linear-additive random utility maximization (RUM) may be insufficient for explaining evacuee behavior. For example, Zeelenberg and Pieters (2007) described that regret aversion is a particularly important determinant of decision making when choices: 1) are perceived by the decision-maker as difficult and important, 2) lead to rapid feedback on choice outcomes, and 3) require accountability. Evacuations and disaster situations fit these criteria well, indicating that evacuees may be more likely to make decisions based on regret minimization than utility maximization.

Consequently, we propose investigating a different decision rule – regret minimization – which assumes that individuals minimize their future regret when making decisions. First, the decision rule, based in regret theory, more closely aligns theoretically with the decision-making process in evacuations. Second, regret minimization assumes that losses are felt more than gains; such semi-compensatory behavior intuitively resonates with the evacuation choice context.

Random regret minimization (RRM) models remain largely absent in evacuation literature beyond several examples using hypothetical stated preference (SP) data (An et al., 2015; Wang et al., 2017). We developed a revealed preference (RP) survey to assess the applicability of regret minimization for *actual* evacuation behavior. RP surveys are often used for contexts with situational and personal constraints such as a dangerous choice environment or emotion-driven choices (Morikawa, 1989; Louviere et al., 2000). RP data also do not exhibit overstating, understating, and indifference biases, which are often present in SP data (Morikawa, 1989; Hausman, 2012). Yet, building a RP choice set for evacuations can be challenging since the attributes, attribute-levels, or alternatives considered by the decision-maker are not always know to the analyst. This is especially problematic for estimating RRM models, as regret is calculated via an attribute-level pairwise comparison with all competing alternatives in the choice set. Moreover, RRM requires a certain level of variation in attribute value differences across alternatives to be able to distinguish non-linear regret from linear utility (since any non-linear function is approximately linear when studied from sufficiently small intervals). In other words, while regret aversion is embodied in the RRM model in terms of a convex value function, limited variation in attributes will not allow the model to infer any regret aversion, even if it is present in the data. In general, to do meaningful RRM model analyses, a dataset must contain:

- At least two considered alternatives in addition to the revealed choice, since RRM and RUM produce the same results on binary choice sets (Chorus, 2010);
- Attributes of the alternatives and numerical values for these alternatives, so that attribute level comparisons across alternatives can be established; and

- Sufficient numerical variation in the attribute levels and in the differences in these levels across alternatives.

With these RRM requirements in mind, we proposed and formalized a RP survey methodology that allows estimation and meaningful comparison of RUM and RRM models in the evacuation behavior context. Using this methodology, we tested our behavioral hypothesis that regret minimization better explains evacuee behavior compared to utility maximization. Finally, we offer methodological and policy recommendations for further developing challenging choice set surveys for RRM and assisting agencies for no-notice and short-notice evacuations.

9.2) Literature

9.2.1) Utility Maximization and Evacuation Behavior

Discrete choice analysis is a modeling technique that uses discrete variables of the decision-maker or alternatives to predict choice (see Ben-Akiva and Lerman, 1985 and Train, 2009 for overviews). Most techniques in these reviews use utility maximization as the primary decision rule, largely because its statistical properties produce relatively simple, accurate, and tractable solutions with a clear connection to welfare economics. The error-inclusive random utility maximization (RUM) model has been the primary behavioral model form across transportation choices, including evacuations. This has included hurricane evacuations (Zhang et al., 2004; Smith and McCarty, 2009; Huang et al., 2012; Murray-Tuite et al., 2012) and wildfire evacuations (Paveglio et al., 2014; McNeill et al., 2015). These studies leverage binary logit models to find factors – often demographics or risk perceptions – that influenced decision making. Other modeled hurricane evacuation choices include transportation mode (Deka and Carnegie (2010), shelter type (Smith and McCarty, 2009; Deka and Carnegie (2010), and route (Akbarzadeh et al., 2015). Wong et al. (2018) reviews hurricane evacuation behavioral modeling and developed RUM models for evacuation choices. Other hurricane evacuation work has extended these models by employing different distributions through a probit model (Solis et al., 2010), creating choice nesting structures through a nested logit (Mesa-Arango et al., 2013), including random parameters through a mixed logit (Sadri et al., 2014; Sarwar et al., 2018), developing dynamic models through a sequential logit (Fu and Wilmot, 2004; Fu et al., 2006), considering decisions as multi-dimensional and joint (Chapter 7), or accounting for different lifestyle preferences through a latent class choice model for tsunamis (Urata and Pel, 2018) and wildfires (McCaffrey et al., 2018). Despite this work, models continue to focus on demographic variables, risk perceptions, or hazard characteristics, not choice attributes.

Despite significant work employing discrete choice modeling for hurricane evacuations, wildfire evacuation behavior remains largely unstudied. Indeed, wildfire behavior likely diverges from behavior during hurricanes and other no-notice hazards (i.e., terrorist attack, chemical release). Early work on wildfire evacuation behavior employed only descriptive statistics, focusing on the decision to evacuate or stay (Fischer III et al., 1995; Benight et al., 2004). More recent research found that a significant proportion of potential evacuees were willing to stay and protect their home (McCaffrey and Winter, 2011). Similarly, some people preferred to defend their home first and evacuate later (McCaffrey and Winter, 2011). This defending behavior is a popular technique in Australia, arising from country-wide fire policies that encouraged a "stay and defend or leave early" (SDLE) approach (McCaffrey and Rhodes, 2009). In the wildfire literature, evacuate or stay/defend is the only key evacuation choice thoroughly investigated through discrete choice modeling (Table 1). Beyond discrete choice analysis, McLennan et al. (2014) developed negative binomial regressions to identify factors that impact wildfire evacuation choice. Despite these advances in applying statistical modeling to understand wildfire behavior, research has not explored other choices beyond evacuate or stay/defend (e.g., route, mode, departure time). Concurrently, most research has only assessed intended decision making for a future wildfire via stated preference and not revealed choices of evacuees. Stated preference has also been used extensively to model choices for no-notice evacuations (i.e., terrorist attack, chemical release). While these studies have explored other choices (e.g., mobilizing trips), the underlying behavior is likely different for wildfires. We also note that while no-notice literature has developed both simple and advanced models in discrete choice such as logit (Liu et al., 2012; Liu et al., 2013), ordered probit (Golshani et al., 2019a), mixed logit (Hsu and Peeta, 2013), and joint (Golshani et al., 2019b) models, all studies continue to use utility maximization. We also note that some work has been conducted on behavior of individuals in building fires (for example Kuligowski and Peacock, 2005; Ronchi and Nilsson, 2013; Kuligowski, 2009; Kuligowski, 2013; Ronchi et al., 2014; Kinsey et al., 2019) with some examples using discrete choice analysis (Lovreglio et al., 2014; Lovreglio et al., 2016). Other unique experimentation research has employed virtual reality to understand evacuee behavior for building fires (Kinateder et al., 2014), tunnel fires (Ronchi et al., 2016), and wildfires (Nguyen et al., 2018). With growing need to evaluate wildfire behavior to improve evacuation outcomes, these other fire studies offer additional methods and behavioral insights that could be integrated and compared with wildfire behavior studies.

Table 1: Summary of Discrete Choice Studies on Wildfire Evacuation Behavior

Authors (Year)	Wildfire(s)	Key Location(s)	N	Model Type	Wildfire Choice
Mozumder et al. (2008)	Hypothetical	East Mountain, Albuquerque, New Mexico	1,018	Binary Probit	Evacuate or Stay/Defend
Paveglio et al. (2014)	Hypothetical	Flathead County, Montana	734	Multinomial Logit	Evacuate or Stay/Defend
McNeill et al. (2015)	Hypothetical	Western Australia	182	Multinomial Logit	Evacuate or Stay/Defend + Delayed Response
Strahan (2017)	Perth Hills Bushfire (2014); Adelaide Hills Bushfire (2015)	Perth Hills, Australia; Adelaide Hills, Australia	429	Binary Logit	Evacuate or Stay/Defend
McCaffrey et al. (2018)	Sample of respondents from different regions with different fire contexts	Horry County, South Carolina; Chelan County, Washington; Montgomery County, Texas	759	Multinomial Logit + Latent Class	Evacuate or Stay/Defend
Toledo et al. (2018)	Haifa Wildfire (2016)	Haifa, Israel	516	Binary Logit	Evacuate or Stay/Defend

9.2.2) Random Regret Minimization (RRM)

To handle the limitations of linear-in-parameters utility maximization models, researchers have developed other decision rules, such as regret minimization. Regret minimization (and the error-inclusive random regret minimization) approach takes the theoretical concepts of regret theory (Loomes and Sugden, 1982) and statistical techniques in discrete choice (Ben-Akiva and Lerman, 1985) to develop a model for multinomial choice sets and multiple attributes in risky or riskless situations (Chorus et al., 2008; Chorus, 2010). Regret minimization models postulate that decision-makers will minimize anticipated regret. Systematic regret is the sum of binary regrets, which are the regrets generated by comparing a considered alternative with another, competing alternative (Chorus, 2010). The convex attribute level regret function generates semi-compensatory behavior where the improvement of one attribute does not necessarily offset the poor qualities of another (and vice versa). The convexity of the regret function postulates that regret (i.e., the emotion which is presumably felt when the competing alternative performs better) receives more weight than so-called rejoice (i.e., the emotion that is presumably felt when the considered alternative performs better). Conceptually, regret aversion presumes that a decision-maker makes a choice based on the avoidance of a negative emotion (Chorus et al., 2008). Practically, the RRM model penalizes poor performing attributes more strongly than a RUM model and rewards so-called compromise alternatives which perform reasonably well on all attributes, over extreme alternatives with a strong performance on some attributes and a poor performance on other attributes (Chorus, 2010). This regret aversion feature of RRM models is conceptually similar to the notion of losses looming larger than gains, which is embedded in loss aversion models. The difference in RRM models is that the attribute levels of competing alternatives form the reference points. In sum, the RRM approach takes the theoretical concepts of regret theories and the statistical techniques in econometrics to align itself with the equally parsimonious structure of traditional RUM models (see Chorus 2012a, 2012b for full overviews). We note that a hybrid RUM-RRM approach that adds demographic characteristics into the model has also been developed (Chorus et al., 2014).

Recently, an extended version of the RRM model has been proposed (Van Cranenburgh et al., 2015). This so-called mu-RRM model has the ability to capture more extreme levels of regret aversion (if present in the data) than the conventional RRM model, and it collapses to a linear RUM model if no regret aversion is present. Furthermore, rather than assuming that decisions are made at the same degree of regret, μRRM models incorporate an estimable regret aversion parameter (μ) that is potentially attribute specific or may differ across decision-makers in different latent classes (Van Cranenburgh et al., 2015). For these latent classes, decision-makers may be divided in terms of the decision rule that best describes their behavior: either mildly or extremely regret-based (RRM) or utility-based (RUM) (Hess et al., 2012; Hess and Stathopoulous, 2013). Recent work developing μRRM models include Sharma et al. (2017) for park-and-ride lot choice and Belgiawan et al. (2017) for multiple transportation choices. Other current research in regret minimization for estimating riskless situations in transportation has included: 1) travel mode (Hensher et al., 2016; Guevara and Fukushi, 2016; Anowar et al., 2019), 2) carsharing (Kim et al., 2017), and 3) vehicle route choice (Prato, 2014; Ramos et al., 2014; Guevara and Fukushi, 2016). An in-depth review of RRM modeling for mode and route choice is presented in Jing et al. (2018). The results of empirical comparisons between RRM and RUM are summarized as follows:

- In about one-third of cases (data-sets, applications), RUM models outperform RRM in model fit and out-of-sample predictions. For the remaining (roughly) two-thirds of cases, models that allow one or more attributes to be processed using RRM-principles perform better. In about half of these cases, a model that presumes RRM for every attribute does best.

- The conventional RRM model (Chorus, 2010) can only generate limited levels of regret aversion and modest potential improvements of model fit. Predictive performance over linear RUM models are generally small. The μRRM model (van Cranenburgh et al., 2015) can capture more extreme levels of regret aversion, leading to potentially large differences in empirical performance compared to RUM models.

9.2.3) RRM and Revealed Preference

Most studies employing RRM have used SP surveys to develop easy-to-compare choice sets with clear alternatives. Since the attributes of alternatives are critical for regret calculation, SP surveys indeed offer the most straightforward tool to compare RRM and RUM models. In a SP design, the modeler can construct alternatives and attributes across randomized choice experiments. Due to the ease of developing SP surveys, relatively little research has analyzed RP surveys for RRM, while it has been reported (Chorus, 2012a) that RRM tends to perform relatively well on RP choice data. However, two key challenges arise with developing an RP survey for estimating RRM models:

1) **Unknown Alternatives:** For RP design, the choice set is not fully known. Since the regret function (also when estimated in logit form) does not exhibit independence of irrelevant alternatives (IIA) properties due to the pairwise comparison of regret across alternatives, knowing the actual choice set is important, although procedures exist to estimate RRM on sampled choice sets (Guevara et al., 2014).
2) **Low Variation of Attribute Levels**: RP surveys do not have systematically varied attribute levels. An individual may have considered choices with rather similar attribute levels, making a small section of the convex regret function indistinguishable from a linear curve.

Some studies have attempted to tackle these challenges. Using RP data on parking choice, Chorus (2010) estimated both RRM and RUM models by asking participants to provide attributes of other parking facilities that they used around campus. Boeri et al. (2012) used a RP survey, where participants rated on a Likert scale from 1 to 5 on variables associated with kayaking sites, but only those they had visited. Similarly, for mode choice, Parthan and Srinivasan (2013) used a Likert scale from 1 to 5 for attributes for chosen and non-chosen modes, finding regret tended to perform better for most mode choice attributes. Prato (2014) estimated RRM and RUM models for route choice using collected data from commuters. The choice set was constructed using a branch and bound algorithm, building two to 19 additional alternatives. Sharma et al. (2019) also used RP data for park-and-ride lot choice. Given a finite number of lots, the research constructed choice sets by imposing several distance constraints to identify alternatives.

9.2.4) Regret in Evacuee Behavior

Currently, it is unclear if RRM models have improved explanatory power for evacuation behavior, compared to linear-additive utility maximization. Several studies have employed regret minimization models but only using SP data (An et al., 2015; Wang et al., 2017). An et al. (2015) focused on mode choice using SP data on an evacuation scenario in Harbin, China. The paper found that the regret-based model performed slightly better than the utility model since it factored in the evacuees' regret aversion (An et al., 2015). Wang et al. (2017) used an SP survey that provided evacuees route choice options with varying average travel times, uncertainty times, possible damage levels, and perceived level of service. A simple regret model and a hybrid regret-utility model performed better than the utility model (Wang et al., 2017).

9.2.5) Key Research Gaps

In light of the literature, three key gaps are clear. First, RRM analysis using RP data remains largely missing with just several exceptions. While SP data are easy to collect and can test future choices or alternatives, on-going debate remains on SP data validity. People could state a preference that differs significantly from actual action (Morikawa, 1989). This may be the case even more so for rare and stressful choice situations, such as evacuations. Second, evacuation behavior research has focused predominately on the following explanatory variables: risk perception, information, hazard characteristics, and demographic characteristics. However, alternative-specific attributes could impact how individuals make a number of different evacuation choices (i.e., departure timing, route, shelter type, transportation mode, reentry timing). For example, the distance of a route (i.e., an attribute of this route) could impact which route is chosen (i.e., the evacuation-related choice). In another example, the safety or cost of an accommodation (i.e., attributes of a shelter type) could impact which shelter is chosen (i.e., the evacuation-related choice). In addition, little work has been conducted on wildfire evacuation behavior. Finally, evacuation behavior analysis has continued to use RUM models, despite intuition and literature from the behavioral sciences that such models may not accurately capture evacuee concerns and worries. Moreover, the type of fully compensatory behavior imposed by linear utility functions commonly used in RUM models may not be representative of behavior in a disaster context; an improvement of an attribute may not offset the poor performance of another. This motivated us to study a regret minimization counterpart of linear RUM models, which postulates semi-compensatory behavior and an overweighting of negative emotions (regret) over positive ones (rejoice).

9.3) Methodology

To fill the research gaps and construct a RP methodology for challenging choice sets, we developed a RP online survey, which captures evacuee choice making and allows us to estimate both RRM and RUM models.

9.3.1) RP Survey Methodology for RRM and RUM

We asked respondents about their choices throughout the evacuation (i.e., evacuate or stay, departure day, departure time of day, route, shelter type, destination, transportation mode, reentry time); demographic information; and willingness to share their transportation and sheltering resources to evacuees. The 183 question RP survey, with substantial skip logic, took a median time of about 47 minutes to complete. Results on sharing resources can be found in Wong and Shaheen (2019). We beta tested the survey in two ways: 1) a similar survey released to individuals impacted by the 2017 Northern California Wildfire (n=79) and 2) a test survey distributed to graduate students (n=4) with varying knowledge of discrete choice modeling. Comments were elicited from both beta tests to improve the survey, particularly related to the choice modeling sections.

Next, we took cues from Boeri et al. (2012) and Parthan and Srinivasan (2013) to develop and *formalize* a RP survey methodology (Figure 1). We reconstruct the choice set to estimate RRM, which requires substantial information about the attributes of alternatives. We note that we used the word "perception" to describe the attributes of alternatives because a respondent may have perceived an attribute differently than the actual conditions. This perception signifies the respondent's observations at the time of their decision. For example, while a respondent may have perceived a high immediate fire danger, they may have been relatively safe (see McCaffrey et al., 2018 for further discussion of perceived risk in the wildfire context). Beta testing uncovered that "perception" was also the easiest way for survey-takers to think about their past decisions, and it did not require extensive background research to determine the actual attributes of alternatives at the time of their decision. A list of all attributes for each alternative can be found in Table 2.

RRM also requires a comparison against multiple alternatives (at least three total alternatives) to adequately calculate systematic regret (Figures 2 and 3). Indeed, a binary RRM model is equivalent to a binary RUM model. To solve this problem, we asked respondents to note their first and second *considered alternative* and the associated attributes. For example, a respondent could respond with:

1. An actual departure time (e.g., Monday, December 4 at 4:00 am) and the attributes associated with that decision;
2. A first considered alternative (e.g., one hour later than their actual choice) and the attributes associated with that alternative; and
3. A second considered alternative (e.g., 30 minutes earlier than their actual choice) and the attributes associated with that alternative.

In this context, a considered alternative was one that was contemplated but not acted upon. For all three question blocks within that choice, the attributes were the same (as seen in Figure 2 and Figure 3). The choice options were either identical, anchored with options that surrounded that choice (e.g., days or hours earlier or later than the actual choice), or open for any answer (e.g., fill-in response). More information regarding exact options offered to the respondent can be found in Table A1 in the Appendix. The same general procedure was conducted for other key evacuation choices (i.e., route, shelter type, transportation mode, and reentry timing). Thus, for each choice, we reconstructed a choice-set of a revealed action and two alternatives (totaling three options).

In this methodology, we did not force responses for the first and second considered alternatives. If a respondent did not consider a first and/or second alternative, they could skip these sections. Moreover, if a respondent did not have an opinion of the attribute of an alternative, they could leave that attribute blank. This survey design was intended to give respondents the most freedom and not constrain answers to merely suit modeling needs. We did not include an option that explicitly stated that the respondent did not consider any other alternatives, which is a limitation of the survey design.

While we recognize that survey design may be error prone due to a respondent's short-term memory, the considered alternatives were the closest proxy we could develop for the RP survey. Moreover, the level of realism remains high since these individuals made real evacuation choices, rather than hypothetical ones as in a SP survey. We also note that we only asked revealed preference questions to evacuees since they made evacuation choices (i.e., departure timing, route, shelter, transportation mode, reentry timing). While we did ask both evacuees and non-evacuees about the attributes of their decision to either evacuate or stay (and their non-chosen alternative), the construction of two alternatives was not suitable for calculating regret as a binary RRM model is the same as a binary RUM model.

Figure 1: RP Survey Methodology for RUM and RRM Models

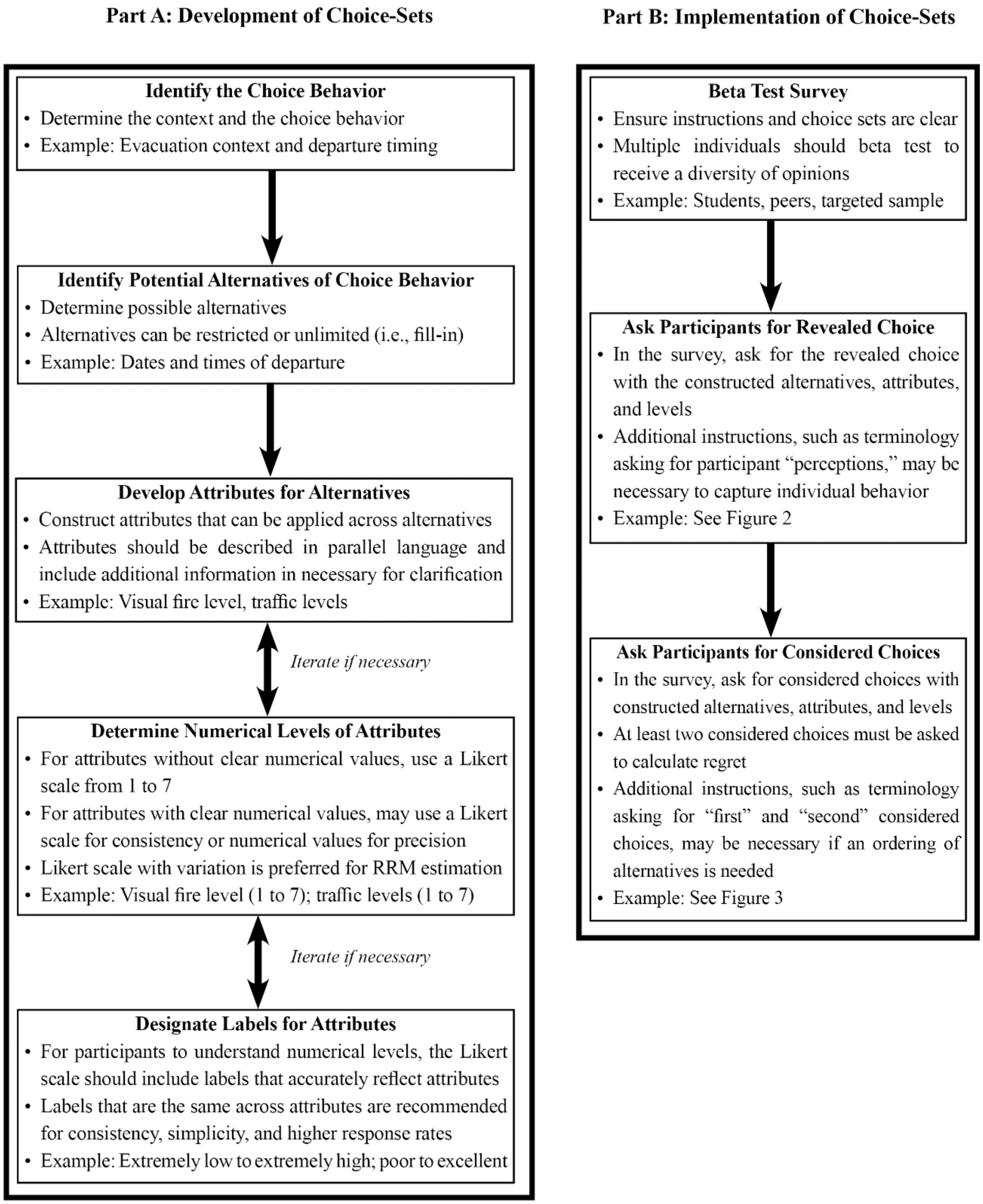


Table 2: List of All Attributes Presented to Survey Respondents for Each Choice

Choice	Attributes of Alternatives
Departure Timing	▪ Immediate danger threat ▪ Visual fire level ▪ Smoke level ▪ Pressure by officials to leave ▪ Pressure by neighbors to leave ▪ Visibility (i.e., from daylight and smoke) ▪ Amount of supplies packed (i.e., water, food, clothes, mementos, etc.) ▪ Uncertainty of escape route safety ▪ Uncertainty of final shelter location ▪ Traffic levels
Route	▪ Distance of route ▪ Time it took to travel the route ▪ Fire danger ▪ Prior experience with the route ▪ Pavement quality ▪ Difficulty in driving (i.e., hilly, winding) ▪ First responder presence (i.e., fire, medical) ▪ Police presence
Mode	▪ Availability/Accessibility ▪ Cost ▪ Comfort ▪ Safety ▪ Speed ▪ Space for luggage
Shelter Type	▪ Comfort ▪ Distance from your residence ▪ Time to travel from your residence ▪ Amenities (i.e., food/water/utilities) ▪ Social Connections ▪ Cost ▪ Safety
Reentry	▪ Confidence that power was available ▪ Confidence that water was available ▪ Traffic levels ▪ Concerns of fire not being put out ▪ Confidence that you would be allowed back to your residence ▪ Pressure to return for work/job ▪ Need to check on residence and belongings ▪ Need to check on other individuals (i.e., family members, friends) ▪ Comfort level at current shelter ▪ Cost of current shelter

Figure 2: Screenshot of Survey Design for Revealed Departure Time

Q36

As a reminder, the largest concentration of wildfires began on December 4th.

Choose the date or the approximate date **you evacuated.**

Monday, Dec. 4 ▼

Q37

What time or approximate time did you evacuate?

12:00 AM ▼

Q38

Did you receive the following evacuation orders at this point in time?

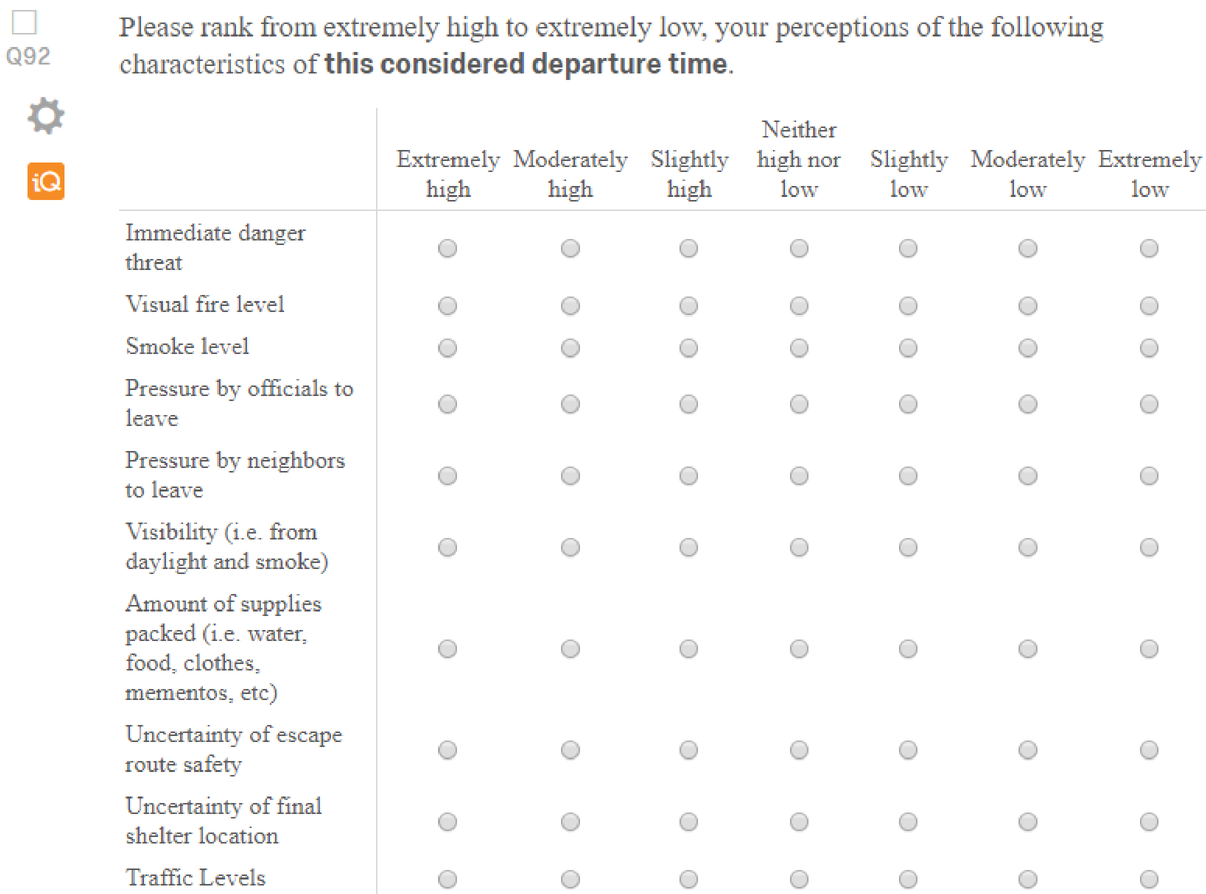
	Yes	No
Mandatory Order	○	○
Voluntary/Recommended Order	○	○
Shelter-in-Place	○	○

Q39

Please rank from extremely high to extremely low, your perceptions of the following characteristics of **your departure time**.

	Extremely high	Moderately high	Slightly high	Neither high nor low	Slightly low	Moderately low	Extremely low
Immediate danger threat	○	○	○	○	○	○	○
Visual fire level	○	○	○	○	○	○	○
Smoke level	○	○	○	○	○	○	○
Pressure by officials to leave	○	○	○	○	○	○	○
Pressure by neighbors to leave	○	○	○	○	○	○	○
Visibility (i.e. from daylight and smoke)	○	○	○	○	○	○	○
Amount of supplies packed (i.e. water, food, clothes, mementos, etc)	○	○	○	○	○	○	○
Uncertainty of escape route safety	○	○	○	○	○	○	○
Uncertainty of final shelter location	○	○	○	○	○	○	○
Traffic Levels	○	○	○	○	○	○	○

Figure 3: Screenshot of Survey Design for Considered Departure Time



Q92

Please rank from extremely high to extremely low, your perceptions of the following characteristics of **this considered departure time**.

	Extremely high	Moderately high	Slightly high	Neither high nor low	Slightly low	Moderately low	Extremely low
Immediate danger threat							
Visual fire level							
Smoke level							
Pressure by officials to leave							
Pressure by neighbors to leave							
Visibility (i.e. from daylight and smoke)							
Amount of supplies packed (i.e. water, food, clothes, mementos, etc)							
Uncertainty of escape route safety							
Uncertainty of final shelter location							
Traffic Levels							

9.3.2) Survey Distribution

We distributed the online survey to individuals impacted by the 2017 December Southern California Wildfires (n=226) between March and July 2018. Both evacuees and non-evacuees from the fires could respond, and only one survey was allowed per household. The wildfires – composed primarily of the Thomas, Creek, Rye, and Skirball Fires – prompted evacuation orders for over 240,000 people across Los Angeles, Ventura, and Santa Barbara counties. The Thomas Fire was the largest fire in California history, burning over 280,000 acres and destroying over 1,000 structures (Cal Fire, 2018). The Thomas Fire broke out on the evening of December 4th around 6:30 pm, caused by high winds that led powerlines owned by Southern California Edison to slap together and drop molten material to the ground (Cal Fire and Ventura County Fire Department, 2019). A few hours later in the early morning of December 5th around 4:00 am, the Creek Fire broke out in Los Angeles County (Mejia and Serna, 2017), followed by the Rye Fire at 9:30 am (ABC7, 2017a) and the smaller Skirball Fire on December 6th at 5:00 am (ABC7, 2017b). The Skirball Fire was caused by an illegal cooking fire (Stewart, 2017), while the cause of the Creek and Rye fires remain unknown.

For distribution, we compiled a list of local agencies, community-based organizations (CBOs), non-governmental organizations (NGOs), and news media organizations in the areas impacted by the wildfires. Types of local agencies included: emergency management, public transit, and transportation agencies. These research partners distributed the survey online via their own networks through various methods including: Facebook, Twitter, listservs, websites, alert subscription services, and news websites. The goal of this distribution was to: 1) reach a wide population of impacted individuals, 2) increase coverage of the survey, and 3) reduce self-selection bias. We also provided an incentive (a chance to win one of five $200 gift cards) to reduce self-selection bias. We note that the survey was not restricted to mandatory or voluntary evacuation zones. Since the survey was also developed to capture other information that was not used in this paper (e.g., the factors influencing the decision to evacuate or stay), we constructed a sample of evacuees and non-evacuees inside and outside evacuation zones.

We received 552 responses of which 303 were finished for a 55% completion rate. We cleaned the data down to 226 responses for modeling, as some respondents did not answer key choice (e.g., evacuate or stay, departure day, departure time of day, route, shelter type, transportation mode, destination, reentry day) and demographic questions (e.g., age, gender, county of residence).

9.3.3) RRM Formulation

For RRM formulation, we followed the methodology from Chorus (2010) for the classical RRM (CRRM) model, Van Cranenburgh et al. (2015) for the μRRM model, and Hess et al. (2012) for the mixed-decision latent class choice model (MDLCCM). Here, we focus entirely on the alternative attributes, not decision-maker characteristics. While demographic variables clearly impact behavior, we aim to identify alternative-specific attributes that could influence behavior for easier comparison between RUM- and RRM-type models. We omit the traditional formulation of RUM and RRM models for brevity, which can be found in detail in Ben-Akiva and Lerman (1985) and Chorus (2010), but we provide the newer μRRM model. A brief overview of the MDLCCM can be found in the Appendix, while a full formulation is provided in Hess et al. (2012).

For the CRRM and μRRM models, systematic regret R for alternative i when compared to all other alternatives j is composed of all binary regret calculations, written as:

$$R_i = \sum_{j \neq i} R_{i \leftrightarrow j} \tag{1}$$

Each binary regret $R_{i \leftrightarrow j}$ is calculated by computing the regret caused by comparing alternative i with alternative j on each attribute and adding together the obtained binary attribute level regrets:

$$R_{i \leftrightarrow j} = \sum_{m=1 \ldots M} R^m_{i \leftrightarrow j} \tag{2}$$

If the attribute m value for alternative i is preferred over that for alternative j (considering the estimated taste parameter sign, where a positive parameter suggests higher values are preferred over lower ones, and vice versa), the regret associated with that attribute and between those alternatives is zero. Otherwise, the regret is based on the attribute value difference, multiplied by the taste parameter:

$$R^m_{i \leftrightarrow j} = \max\{0 + v_{0m}, \beta_m \cdot (x_{jm} - x_{im}) + v_{xm}\} \tag{3}$$

Here, β_m is the estimated taste parameter (i.e., coefficient) for attribute m. Van Cranenburgh et al., (2015) extend this using an estimable regret parameter μ, which represents the regret aversion level. We assume that the error term v inside the max-operator follows an i.i.d. Extreme Value Type I distribution with variance equaling:

$$var(v) = (\pi^2/6) \cdot \mu^2 \tag{4}$$

After integrating the error term in equation (3) to replace the maximum-operator by its expected maximum, we now have the logsum-based formulation of random regret:

$$R_i^{\mu} = \sum_{i \neq j} \sum_{m=1 \ldots M} \mu \cdot \ln\left(1 + \exp\left(\frac{\beta_m}{\mu}[x_{jm} - x_{im}]\right)\right) \tag{5}$$

Adding random errors to this systematic regret and assuming that their negative value follows a conventional i.i.d. EV Type I distribution, the popular logit-type formulations for choice probabilities are obtained:

$$P_i^{\mu} = \frac{\exp(-R_i^{\mu})}{\sum_{j=1 \ldots J} \exp(-R_j^{\mu})} \tag{6}$$

As noted in Van Cranenburgh et al. (2015), the estimable regret aversion parameter value has three special cases:

1) If μ is equal to one, the μRRM model is equivalent to the CRRM model proposed in Chorus (2010).
2) If μ is arbitrarily close to zero, the μRRM model exhibits very strong regret minimizing behavior (i.e., a large asymmetry between regret and rejoice, the former being overweighted).
3) If μ is arbitrarily large (typically values larger than five), the μRRM model exhibits linear utility maximizing behavior, where no overweighting of regret takes place.

9.4) Results and Discussion

Using survey data from the 2017 December Southern California Wildfires (Table 3), we developed several models of evacuation choice (i.e., dependent variable) focusing on: 1) departure timing (n=118), 2) route choice (n=93), 3) shelter type (n=118), 4) transportation mode choice (n=70), and 5) reentry timing (n=89). Each choice has a different sample size, depending on response rates. While 175 individuals evacuated, only a subset answered all *considered choices*. For each choice, we developed and tested four models:

1) A classical RUM model;
2) A classical RRM model;
3) A general μRRM model; and
4) An attribute-specific μRRM model.

All models were developed and analyzed in Python through the package Biogeme (Bierlaire, 2003). We developed both the RUM and RRM models using generic parameters. Thus, an estimated coefficient reflects the impact of that attribute (i.e., independent variable) across any alternative (i.e., not alternative-specific). Results are shown in Table 4 to 8 for departure timing, route choice, shelter choice, transportation mode choice, and reentry timing (see below for detailed reporting and interpretation of results). In addition to these four models, we also tested a mixed-decision latent class choice model for all choices but found only weakly regret-averse behaviors for route choice and transportation mode choice (Table 9 and 10), indicating the need for future exploration. To qualify all results – which found minimal regret-minimizing behavior – we provide discussion about the limitations of the survey and overall methodology in Section 5. The results do not tell us definitive conclusions as to why regret aversion is not found in our models but rather provide possible explanations.

Table 3: Demographics and Choices of 2017 December California Wildfire Survey

Individual Characteristics (n=226)			
Gender		**Employment**	
Male	26.1%	Employed full time	57.1%
Female	73.9%	Employed part time	11.9%
		Unemployed looking for work	4.9%
Age		Retired	22.1%
18-24	2.7%	Student	2.2%
25-34	17.7%	Disabled	1.3%
35-44	15.0%	Prefer not to answer	0.4%
45-54	19.0%		
55-64	26.5%	**Primary Transportation Mode for Work/School**	
65+	19.0%	Drive alone using a car, SUV, pickup, or van	87.6%
		Carpool/vanpool	2.2%
Race		Rail (e.g., light/heavy, subway/metro, trolley)	0.9%
Asian	2.7%	Bus	1.8%
Black or African-American	0.4%	Motorcycle/scooter	0.9%
Mixed	7.5%	Bicycle	0.9%
Native American/Alaska Native	0.4%	Walk	0.4%
Pacific Islander	0.9%	Work from home	1.8%
White	81.4%	Other	0.9%
Other	4.0%	Prefer not to answer/No answer	2.7%
Prefer not to answer	2.7%		
		Previous Evacuee*	
Ethnicity		Yes	35.3%
Hispanic	11.1%	No	64.7%
Not Hispanic	76.1%		
Prefer not to answer	12.8%	**Previous Wildfire Experience****	
		Yes	93.4%
Education		No	6.6%
Less than high school	0.0%		
High school graduate	0.9%	**Mobile Phone Type**	
Some college	15.9%	Do not own a mobile phone	2.7%
2-year degree	5.8%	Own a typical mobile phone (non-smartphone)	5.3%
4-year degree	41.2%	Own a smartphone	92.0%
Professional degree	28.3%		
Doctorate	8.0%	**In-Vehicle or Smartphone Navigation*****	
Prefer not to answer	0.0%	Yes	79.6%
		No	20.4%

Household Characteristics (n=226)			
Current County of Residence		**Home Ownership†**	
Ventura	43.8%	Yes	67.3%
Santa Barbara	41.6%	No	29.6%
Los Angeles	13.3%	Prefer not to answer	3.1%
Other California	1.3%		
		Live in Cal Fire High Risk Area††	
Displacement after Wildfire		Yes	38.1%
Same Residence	88.9%	No	28.8%
Different Residence or Not Returned	10.6%	I don't know	33.2%
No answer	0.4%		
		Current Household Characteristics	
Length of Residence†		Household with Disabled	14.2%
Less than 6 months	5.8%	Household with Children	25.2%
6 to 11 months	4.9%	Household with Older Adults	28.3%
1 to 2 years	12.4%	Households with Pets	63.7%
3 to 4 years	14.6%		
5 to 6 years	7.1%	**Household Income (2017)**	
7 to 8 years	5.3%	Less than $10,000	0.4%
9 to 10 years	4.9%	$10,000 - $14,999	1.3%
More than 10 years	45.1%	$15,000 - $24,999	2.2%
		$25,000 - $34,999	2.2%
Residence Structure†		$35,000 - $49,999	6.2%
Site build (single home)	73.9%	$50,000 - $74,999	14.6%
Site build (apartment)	19.5%	$75,000 - $99,999	11.5%
Mobile/manufactured home	6.2%	$100,000 - $149,999	21.2%
Prefer not to answer	0.4%	$150,000 - $199,999	13.3%
		$200,000 or more	14.2%
		Prefer not to answer	12.8%

Evacuation Choices (n=175)			
Evacuation Choice (n=226)		**Usage of GPS for Routing**	
Evacuated	77.4%	Yes, and followed route	18.3%
Did Not Evacuate	22.6%	Yes, but rarely followed route	4.6%
		No	77.1%
Departure Date			
Monday, Dec. 4	32.6%	**Multiple Destinations**	
Tuesday, Dec. 5	28.6%	Sheltered in more than one location	41.7%
Wednesday, Dec. 6	5.1%	Sheltered in one location	58.3%
Thursday, Dec. 7	4.0%		
Friday, Dec. 8	4.6%	**Within County Evacuation**	
Saturday, Dec. 9	3.4%	Yes	66.3%
Sunday, Dec. 10	8.0%	No	33.7%
After Sunday, Dec. 10	13.7%		
		Mode Choice	
Departure Timing by Hour		One personal vehicle	45.1%

12:00 AM - 5:59 AM	23.4%	Two personal vehicles	40.6%
6:00 AM - 11:59 AM	24.6%	More than two personal vehicles	8.6%
12:00 PM - 5:59 PM	24.6%	Aircraft	0.6%
6:00 PM - 11:59 PM	27.4%	Rental car	0.6%
		Recreational vehicle (RV)	1.1%
Shelter Type		Truck and trailer	2.3%
A friend's residence	30.3%	Non-household carpool	1.1%
A family member's residence	32.6%		
A hotel or motel	22.9%	**Reentry Date**	
A public shelter	3.4%	Tuesday, Dec. 5	4.9%
A second residence	2.9%	Wednesday, Dec. 6	9.9%
A portable vehicle (e.g., RV)	4.0%	Thursday, Dec. 7	4.9%
Peer-to-peer service (e.g., Airbnb)	1.1%	Friday, Dec. 8	11.7%
Other	2.9%	Saturday, Dec. 9	8.0%
		Sunday, Dec. 10	6.2%
Primary Route by Road Type		Monday, Dec. 11	4.3%
Highways	62.3%	Tuesday, Dec. 12	3.1%
Major Roads	15.4%	Wednesday, Dec. 13	3.1%
Local Roads	4.0%	Thursday, Dec. 14	3.7%
Rural Roads	1.1%	Friday, Dec. 15	2.5%
No Majority Type	17.1%	Saturday, Dec. 16	1.2%
		Sunday, Dec. 17	4.3%
		After Sunday, Dec. 17	32.1%

* “How many times have you evacuated from any residence prior to this disaster?”
** “How many times have you experienced a wildfire?”
*** Under normal conditions

† At the time of the wildfire
†† At the time of the wildfire and very high or high fire severity zone as defined by the California Department of Forestry and Fire Protection

Note: Percentages may not add to 100% due to rounding

Table 4A: Discrete Choice Modeling Results for Departure Time (n=118)

	RUM Model				CRRM Model			
	Coef.	Std. Error	p-value		Coef.	Std. Error	p-value	
Immediate Danger Threat	-0.57	0.16	<0.01	***	-0.32	0.10	<0.01	***
Pressure from Neighbors to Leave	0.43	0.14	<0.01	***	0.28	0.09	<0.01	***
Pressure from Officials to Leave	0.13	0.10	0.19		0.07	0.06	0.25	
Uncertainty of Escape Route	-0.27	0.11	0.01	**	-0.16	0.06	0.01	**
Smoke Level	0.20	0.18	0.28		0.13	0.11	0.26	
Amount of Supplies Packed (i.e., water, food, clothes, mementos)	0.01	0.10	0.92		0.02	0.06	0.80	
Traffic Levels	-0.16	0.12	0.19		-0.09	0.07	0.20	
Visibility (i.e., from daylight and smoke)	0.24	0.12	0.04	*	0.13	0.07	0.06	†
Visual Fire Level	0.50	0.19	0.01	**	0.29	0.12	0.01	**
Final log likelihood:	-103.6				-105.7			
Rho-square:	0.19				0.18			
Adjusted rho-square:	0.12				0.11			

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

Table 4B: Discrete Choice Modeling Results for Departure Time (n=118)

	uRRM Model				Attribute-Specific uRRM Model			
	Coef.	Std. Error	p-value		Coef.	Std. Error	p-value	
Immediate Danger Threat	-0.38	0.11	<0.01	***	-0.37	0.11	<0.01	***
Pressure from Neighbors to Leave	0.29	0.09	<0.01	***	0.29	0.09	<0.01	***
Pressure from Officials to Leave	0.09	0.07	0.19		0.08	0.07	0.20	
Uncertainty of Escape Route	-0.18	0.07	0.01	**	-0.18	0.07	0.01	**
Smoke Level	0.13	0.12	0.28		0.14	0.12	0.27	
Amount of Supplies Packed (i.e., water, food, clothes, mementos)	0.01	0.07	0.92		0.01	0.07	0.91	
Traffic Levels	-0.11	0.08	0.19		-0.11	0.08	0.19	
Visibility (i.e., from daylight and smoke)	0.16	0.08	0.04	*	0.16	0.08	0.04	*
Visual Fire Level	0.33	0.13	0.01	**	0.33	0.13	0.01	**
mu (generic across attributes)	>>10.00	>>10.00	0.95					
mu Visual Fire Level					2.23	13.8	0.87	
Final log likelihood:	-103.6				-103.8			
Rho-square:	0.19				0.19			
Adjusted rho-square:	0.12				0.12			

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

Table 5A: Discrete Choice Modeling Results for Route Choice (n=93)

Route Choice (n=93)	**RUM Model**				**CRRM Model**			
	Coef.	Std. Error	p-value		Coef.	Std. Error	p-value	
Difficulty in Driving (i.e., hilly, winding)	-0.12	0.11	0.26		-0.08	0.07	0.23	
Distance of Route	-0.33	0.13	0.01	**	-0.19	0.08	0.01	**
Prior Experience with Route	0.16	0.13	0.20		0.11	0.09	0.20	
Fire Danger	-0.36	0.13	0.01	**	-0.24	0.09	0.01	**
First Responder Presence (i.e., fire, medical)	-0.45	0.30	0.13		-0.15	0.11	0.17	
Police Presence	0.16	0.31	0.59		-0.03	0.11	0.80	
Pavement Condition	0.49	0.16	<0.01	***	0.32	0.11	<0.01	***
Final log likelihood:	-76.0				-77.5			
Rho-square:	0.26				0.24			
Adjusted rho-square:	0.19				0.18			

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

Table 5B: Discrete Choice Modeling Results for Route Choice (n=93)

Route Choice (n=93)	**uRRM Model**				**Attribute-Specific uRRM Model**			
	Coef.	Std. Error	p-value		Coef.	Std. Error	p-value	
Difficulty in Driving (i.e., hilly, winding)	-0.08	0.07	0.26		-0.08	0.07	0.24	
Distance of Route	-0.22	0.08	0.01	**	-0.22	0.08	0.01	**
Prior Experience with Route	0.11	0.08	0.20		0.11	0.08	0.19	
Fire Danger	-0.24	0.09	0.01	**	-0.25	0.09	0.01	**
First Responder Presence (i.e., fire, medical)	-0.30	0.20	0.13		-0.27	0.18	0.12	
Police Presence	0.11	0.20	0.59		0.08	0.18	0.65	
Pavement Condition	0.33	0.11	<0.01	***	0.33	0.11	<0.01	***
mu (generic across attributes)	>>10.00	>>10.00	1.00					
mu Fire Danger					0.59	0.989	0.55	
Final log likelihood:	-76.0				-76.0			
Rho-square:	0.26				0.26			
Adjusted rho-square:	0.18				0.18			

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

Table 6A: Discrete Choice Modeling Results for Shelter Choice (n=118)

Shelter Choice (n=118)	Full RUM Model				CRRM Model			
	Coef.	Std. Error	p-value		Coef.	Std. Error	p-value	
Amenities	0.07	0.12	0.52		0.05	0.07	0.50	
Comfort	0.07	0.11	0.51		0.05	0.07	0.48	
Cost	-0.05	0.08	0.50		-0.04	0.05	0.45	
Distance Away	-0.11	0.09	0.21		-0.07	0.06	0.21	
Safety	0.35	0.12	<0.01	**	0.22	0.08	<0.01	**
Social Connections	0.11	0.09	0.20		0.07	0.05	0.20	
Final log likelihood:	-116.1				-116.4			
Rho-square:	0.10				0.10			
Adjusted rho-square:	0.06				0.06			

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

Table 6B: Discrete Choice Modeling Results for Shelter Choice (n=118)

Shelter Choice (n=118)	uRRM Model				Attribute-Specific uRRM Model (No Regret Found)			
	Coef.	Std. Error	p-value		Coef.	Std. Error	p-value	
Amenities	0.05	0.08	0.52		0.05	0.08	0.52	
Comfort	0.05	0.07	0.51		0.05	0.07	0.51	
Cost	-0.03	0.05	0.50		-0.03	0.05	0.50	
Distance Away	-0.07	0.06	0.21		-0.07	0.06	0.21	
Safety	0.23	0.08	<0.01	**	0.23	0.08	<0.01	**
Social Connections	0.07	0.06	0.20		0.07	0.06	0.20	
mu (generic across attributes)	>>10.00	>>10.00	0.95					
Final log likelihood:	-116.1				-116.2			
Rho-square:	0.10				0.10			
Adjusted rho-square:	0.05				0.06			

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

Table 7A: Discrete Choice Modeling Results for Mode Choice (n=70)

Mode Choice (n=70)	Full RUM Model			CRRM Model		
	Coef.	Std. Error	p-value	Coef.	Std. Error	p-value
Availability	0.15	0.13	0.27	0.08	0.08	0.28
Cost	-0.12	0.12	0.32	-0.07	0.08	0.36
Safety	0.11	0.15	0.47	0.07	0.09	0.39
Speed	0.09	0.15	0.54	0.05	0.08	0.52
Final log likelihood:	-73.4			-73.6		
Rho-square:	0.05			0.04		
Adjusted rho-square:	-0.01			-0.01		

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

Table 7B: Discrete Choice Modeling Results for Mode Choice (n=70)

Mode Choice (n=70)	**uRRM Model**			**Attribute-Specific uRRM Model (No Regret Found)**		
	Coef.	Std. Error	p-value	Coef.	Std. Error	p-value
Availability	0.09	0.09	0.27	0.15	0.13	0.27
Cost	-0.08	0.08	0.32	-0.12	0.12	0.32
Safety	0.07	0.10	0.47	0.11	0.15	0.47
Speed	0.06	0.10	0.54	0.09	0.15	0.54
mu (generic across attributes)	>>10.00	>>10.00	1.00			
Final log likelihood:	-73.4			-73.34		
Rho-square:	0.05			0.05		
Adjusted rho-square:	-0.02			-0.01		

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

Table 8A: Discrete Choice Modeling Results for Reentry Choice (n=89)

Reentry Choice (n=89)	**Full RUM Model**				**CRRM Model**			
	Coef.	**Std. Error**	**p-value**		**Coef.**	**Std. Error**	**p-value**	
Allowed to Return	0.23	0.12	0.04	*	0.17	0.08	0.04	*
Concerns of Fire Still Burning	-0.10	0.10	0.35		-0.05	0.07	0.42	
Cost of Current Shelter	0.13	0.11	0.24		0.07	0.07	0.26	
Need to Check on People	0.25	0.15	0.08	†	0.16	0.09	0.10	†
Need to Check Residence	0.22	0.18	0.24		0.14	0.12	0.25	
Comfort of Current Shelter	-0.18	0.13	0.15		-0.10	0.08	0.19	
Confidence of Power Availability	0.01	0.15	0.93		0.01	0.11	0.91	
Pressure to Return to Job/Work	0.03	0.17	0.86		0.01	0.10	0.91	
Final log likelihood:	-86.8				-87.2			
Rho-square:	0.11				0.11			
Adjusted rho-square:	0.03				0.03			

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

Table 8B: Discrete Choice Modeling Results for Reentry Choice (n=89)

Reentry Choice (n=89)	**uRRM Model**				**Attribute-Specific uRRM Model**			
	Coef.	**Std. Error**	**p-value**		**Coef.**	**Std. Error**	**p-value**	
Allowed to Return	0.16	0.08	0.04	*	0.18	0.09	0.04	*
Concerns of Fire Still Burning	-0.06	0.07	0.35		-0.06	0.07	0.37	
Cost of Current Shelter	0.09	0.07	0.24		0.09	0.07	0.21	
Need to Check on People	0.17	0.10	0.08	†	0.17	0.10	0.08	†
Need to Check Residence	0.14	0.12	0.24		0.14	0.12	0.27	
Comfort of Current Shelter	-0.12	0.08	0.15		-0.12	0.08	0.16	

Confidence of Power Availability	0.01	0.10	0.93	0.01	0.11	0.96
Pressure to Return to Job/Work	0.02	0.11	0.86	0.02	0.11	0.86
mu (generic across attributes)	>>10.00	>>10.00	0.98			
mu Allowed to Return				0.31	0.49	0.53
mu Pressure to Return to Job/Work				1.65	31.00	0.96
Final log likelihood:	-86.9			-86.6		
Rho-square:	0.11			0.11		
Adjusted rho-square:	0.02			0.01		

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

Table 9: Mixed-Decision Latent Class Choice Models for Route

Route Choice (n=93)	RUM Latent Class Model				uRRM Latent Class Model			
Class 1	Coef.	Std. Error	p-value		Coef.	Std. Error	p-value	
Difficulty in Driving (i.e., hilly, winding)	0.11	0.36	0.77		0.10	0.16	0.54	
Distance of Route	-1.09	0.94	0.24		-0.75	0.27	<0.01	***
Fire Danger	-0.17	0.25	0.48		-0.11	0.18	0.54	
First Responder Presence (i.e., fire, medical)	0.41	0.51	0.42		-1.33	0.67	0.05	*
Pavement Condition	0.65	0.47	0.17		0.39	0.21	0.07	†
mu (generic across attributes)					2.32	4.85	0.63	
Class 2	Coef.	Std. Error	p-value		Coef.	Std. Error	p-value	
Difficulty in Driving (i.e., hilly, winding)	0.01	0.39	0.98		-0.19	0.27	0.50	
Distance of Route	0.28	0.85	0.74		2.64	0.97	0.01	**
Fire Danger	-0.87	0.48	0.07	†	-4.42	1.88	0.02	*
First Responder Presence (i.e., fire, medical)	-1.91	0.98	0.05	*	7.68	2.98	0.01	**
Pavement Condition	1.47	0.78	0.06	†	8.40	3.51	0.02	*
mu (generic across attributes)					>>10.00	>>10.00		
Percentage Class 1	39.4%				65.7%			
Percentage Class 2	60.6%				34.3%			
Final log likelihood:	-71.52				-67.38			
Rho-square:	0.30				0.34			
Adjusted rho-square:	0.19				0.21			

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

Table 10: Mixed-Decision Latent Class Choice Models for Mode

Mode (n=70)	RUM Latent Class Model				uRRM Latent Class Model			
Class 1	Coef.	Std. Error	p-value		Coef.	Std. Error	p-value	
Availability	4.70	3.03	0.12		2.47	1.47	0.09	†
Cost	0.49	0.28	0.09	†	0.48	0.32	0.13	
Safety	-1.09	0.69	0.11		-0.37	0.29	0.20	
Speed	2.28	1.22	0.06	†	0.82	0.49	0.10	†
mu (generic across attributes)					>>10.00	>>10.00		

Class 2	Coef.	Std. Error	p-value		Coef.	Std. Error	p-value
Availability	-2.50	1.61	0.12		-4.59	3.99	0.25
Cost	-1.77	1.35	0.19		-1.56	1.18	0.19
Safety	7.24	4.36	0.10	†	0.73	0.78	0.35
Speed	-6.92	4.20	0.10	†	-0.05	0.58	0.93
mu (generic across attributes)					2.50	4.20	0.55
Percentage Class 1	63.1%				62.8%		
Percentage Class 2	36.9%				37.2%		
Final log likelihood:	-59.8				-60.9		
Rho-square:	0.22				0.21		
Adjusted rho-square:	0.11				0.06		

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

9.4.1) Departure Timing Choice

When estimating factors impacting departure timing in the RUM model, we find that immediate danger and escape route uncertainty to be significant and negative. Individuals are more likely to choose departure times when the fire threat is lower. Evacuees may also wait for routing information from officials before leaving. We find that higher pressure from neighbors increases individuals desire to leave at a specific departure time, indicating the role of peer influence. Lower visibility (i.e., from smoke or nighttime) is associated with a lower likelihood to depart at the chosen departure time. Finally, visual fire level is positive and significant, indicating that evacuees chose departure times when the visual fire is high. This result most likely stems from the evacuation context of the 2017 Southern California Wildfires, when some evacuees had just minutes to evacuate. Hence, the "choice" may have only contained one alternative – evacuate immediately – and the results are not necessarily a reflection of "preference." We note that the perception of visual fire is measured here (i.e., intense fire cues from the environment), which likely increases evacuees' risk perception. Other research (such as Strahan, 2017 and Toledo et al., 2018) has found that environmental cues impact the decision to evacuate or stay/defend, and our models also indicate the importance of environmental cues for *when to evacuate*. Overall, we find parallel results in the CRRM model but a slightly lower fit, indicating no regret minimizing behavior. We then estimated a μRRM model but found no regret-based behavior. The results suggest that individuals are not minimizing regret across the entire choice context (including all variables). This might be because departure time consists of context-specific and variable-specific considerations (such as the tradeoff between life and property safety). This can be partially seen through the attribute-specific μRRM model, which finds weak regret-minimizing behavior for visual fire level. The results suggest that losses are felt more than gains for visual fire level, which may be associated with the Protective Action Decision Model (PADM) or risk aversion (McCaffrey et al., 2018). Indeed, extreme perceptions (very high fire level or very low fire level) may not be preferable since they correspond to potential death and high inconvenience, respectively. The attribute of visual fire level may also be "difficult" to assess. Overall, however, these results indicate that departure timing in this evacuation context exhibits mostly utility-maximizing behavior. Additional reasons for this behavior, which may be due to the survey construction and methodology, are presented later in the limitations section (Section 5).

9.4.2) Route Choice

Similar to departure timing, we find several significant attributes. Evacuees prefer routes that are shorter (i.e., lower distance) and have less surrounding fire (i.e., lower fire danger). These results are intuitive but have important implications for transportation response. First, traffic control should be focused predominately on neighborhoods close to the fire. Second, individuals preferred routes that were shorter by distance (and likely by travel time). To find these routes, some evacuees may use route-based navigation tools (e.g., Google Maps, Waze), which could at their best improve evacuation clearance times and their worst lead people down dangerous routes. We also find that individuals prefer routes with good pavement conditions, indicating additional traffic on recently paved roads. We find similar results for the CRRM model, and no general regret-minimizing behavior in the μRRM model. Similar to departure timing, some attributes may be processed in a regret-minimizing fashion. Indeed, we find rather strong regret-minimizing behavior for fire danger, suggesting that individuals feel losses more than gains. This is intuitive as high fire danger is both risky for safety reasons and difficult for emotional reasons. For the MDLCCM (Table 9), we find a class with weak regret-minimization. This class prefers very short routes, and its members would experience significant regret if the route was longer. The behavior could be related to wanting to remain close by to monitor the fire or reduce travel time on the route. However, it is not immediately clear why this regret-minimizing class prefers not to have first-responders available. One possibility is that this class may have thought that additional vehicles on the route would lead to increased congestion, which would increase their losses. We also note that all parameters improve in terms of their significance from the baseline RUM-only LCCM, leading the MDLCCM to have a stronger fit. This result suggests that a strong utility-maximizing class exists, and a division between decision rules may be appropriate for route choice.

9.4.3) Shelter Choice

In the RUM estimation, we only find safety to be significant. In the survey, we did not provide additional clarification on safety, which could refer to individuals' perception of fire safety or safety from other people. Regardless, the results indicate that public shelters should be out of fire danger and monitored closely by security personnel or volunteers. The same result is found for the CRRM model, but the fit does not improve. We again find no general regret-minimizing behavior in the μRRM model, and we also did not find attribute-specific regret. Finally, we did not find a regret-minimizing class for the MDLCCM. Overall, we are unable to further speculate why we did not find regret-minimizing behavior beyond limitations in the survey design and methodology (see Section 5 for discussion). We recommend that future work continue to assess shelter decision-making to determine if behavior is regret-minimizing. We also note that the relatively poor mode fit of the shelter choice model overall indicates that the choice may be more dependent on demographics, availability, and evacuation experiences (as seen in Whitehead 2000; Smith and McCarty 2009; Deka and Carnegie 2010; Mesa-Arango et al. 2013; Wong et al. 2018) than attributes of the accommodation.

9.4.4) Transportation Mode Choice

For mode choice, we developed a RUM model using availability, cost, safety, and speed. However, we find that all attributes were insignificant, indicating that modal choice may be influenced more by demographic variables (i.e., vehicle ownership) or evacuation experience as was found in Deka and Carnegie (2010), Sadri et al. (2014), and Wong et al. (2018). We do not find the results improve by estimating the three variations of RRM models. However, we do find a weak regret-minimizing class of individuals from the MDLCCM model in Table 10. We note that we do not know for certain what mechanisms are influencing this regret-based decision-making on mode. One possibility is that individuals may be minimizing their regret related to their mode choice based on safety (which is positive, albeit slightly insignificant, in the model for the regret class). Some evacuees may have wanted to take one vehicle to keep the household together, thus minimizing regret related to household safety. We also note that a RUM-only MDLCCM yields more significant attribute coefficients.

9.4.5) Reentry Timing Choice

Finally, we estimated models for reentry timing choice. For the RUM and CRRM models, we find being allowed to return as the only significant variable (but wanting to check on other people was slightly insignificant). This indicates that evacuees may wait for official orders of repopulation before returning, an intuitive result. We note that reentry timing should be highly dependent on official orders to return. However, this is not always the case. For example, some evacuees attempted to return prior to official orders during other wildfires (Serna et al., 2017). Research in hurricane evacuations has found that the source of reentry information is only weakly correlated with reentry compliance (Lin et al., 2014). Consequently, return information from official orders is not necessarily required for reentry. The analog to this is that a mandatory evacuation order is not necessary for an individual to evacuate or choose a departure time. Moreover, some evacuees may not return immediately when the evacuations are lifted, as they may fear fire danger or the lack of power. These reentry nuances prompted us to test different attributes of reentry timing, but further investigation of these attributes is needed in future work. We did not find any regret-minimizing behavior from the CRRM model or μRRM model when a generic regret aversion parameter is estimated, but we hypothesize that regret may be more present at the attribute-level. Indeed, we find strong regret minimizing behavior for being allowed to return and weak regret aversion for pressure from job/work. In an evacuation context, individuals may regret returning too early (i.e., leading to an extra trip) or returning too late (i.e., reducing time at home). For job/work pressure, evacuees may experience regret associated with lost income, if they do not return on time (or early).

9.5) Limitations

This paper has several limitations, including the survey distribution method. The survey has self-selection bias as individuals opt into the survey. We attempted to reduce this self-selection bias by distributing the survey through multiple partnering agencies and news media and by providing an incentive. The survey was also distributed online, and only individuals with access to the Internet were able to participate, causing us to under sample those without technology. We over sampled households that own vehicles (potentially impacting mode choice results), females, white individuals, and wealthy households. We acknowledge that future online surveys – which are necessary for complex RUM and RRM estimation – should attempt to reduce sampling bias through effective (but costly) randomized sampling. Finally, we note that the estimated models contain a small sample size, which inhibits conclusions drawn from the results.

Throughout the development of our RP survey methodology and analysis, we found several important limitations to our methodology, which should be addressed.

1) **Single Data Point Per Person:** Since each individual only provided a revealed choice and two considered choices, we only retrieved a single data point per individual.
2) **Considered Choice Opt-Out:** Some individuals did not ponder other choices beyond their revealed choice and opted out of answering the considered choice questions. Consequently, we were unable to estimate regret, which lowered our sample size.
3) **Attribute-Level Opt-Out:** Some respondents never selected an attribute level for some choices. This also prevented us from estimating regret, decreasing our sample size.
4) **Low Attribute-Level Variation**: While we set the Likert scale from 1 to 7, some individuals rated the attribute the same or similarly across their revealed and two considered choices. This causes issues in estimating regret, biasing results toward RUM.

We also did not estimate hybrid RUM-RRM models in which some attributes are treated as regret-attributes and others as utility-attributes (Chorus et al., 2013), and we did not account for demographics (which in principle can be covered in RRM models and more easily in Hybrid RUM-RRM models). We opted against this, as we aimed to more directly compare RUM and RRM models and identify the attribute-level impacts (if any) on evacuation choice making. Future research that focuses on the policy implications of evacuation behavior models should include demographics. Related to attributes, even though we provided and tested a number of attributes for each choice, they may not be the most salient ones that impact decision-making. For example, in the departure timing context, regret may be most present for attributes related to balancing life safety and property protection, which we did not explore in the survey. Other attributes should be addressed in future surveys to improve assessment of regret in an RP evacuation context.

Finally, we note that the resulting regret functions are (close to) linear for small sections, as is illustrated in Figure 4, where we plot a regret function for the example of departure timing. We calculated all absolute pairwise differences between attribute levels for the chosen and considered choices (Figure 5) and found that many differences are very small (0 or 1 point). This implies that even if regret aversion exists in the behavior, it would be unrecognizable for the small sections that are (close to) linear in the regret functions.

Figure 4: Regret Functions for Departure Timing Example

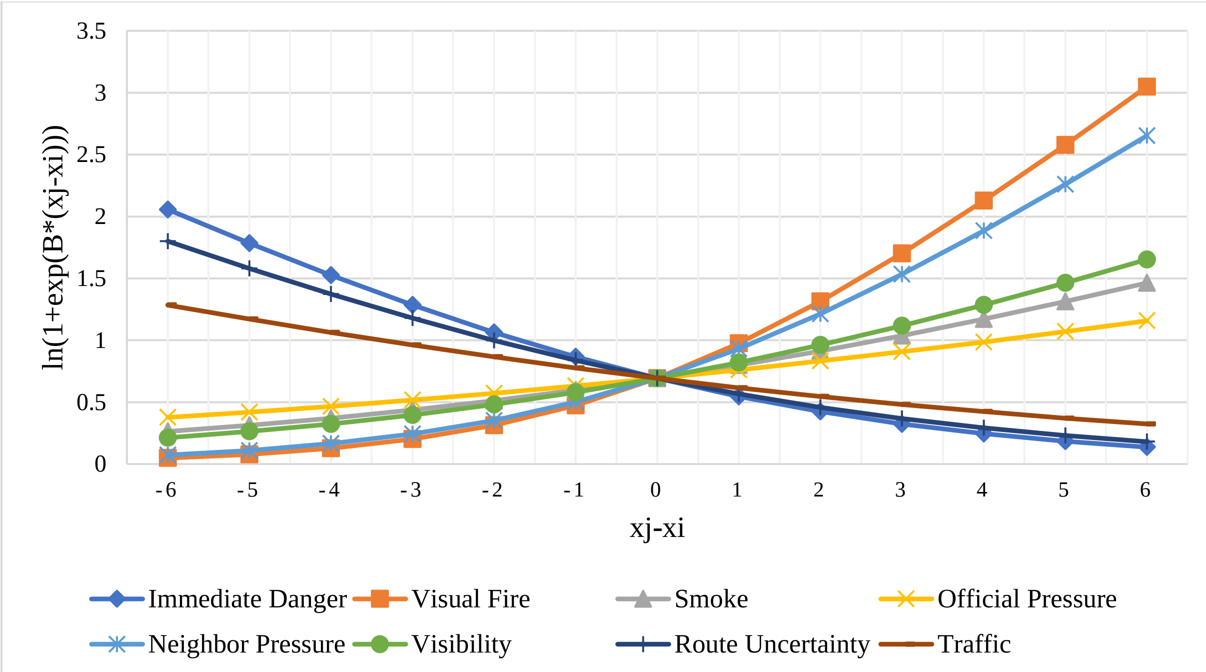
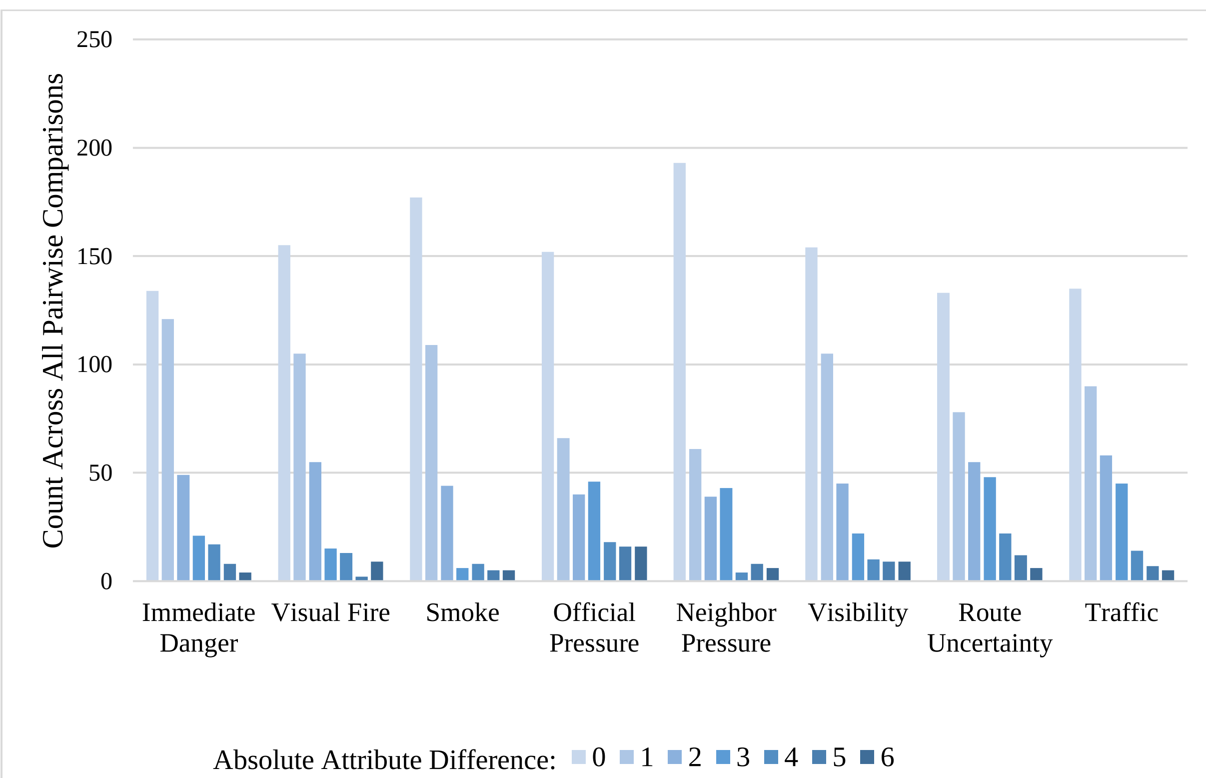


Figure 5: Histogram of Absolute Attribute Differences Across All Pairwise Regret Comparisons for Departure Timing Example



9.6) Recommendations

For our recommendations, we provide several improvements for developing RP surveys for RUM and RRM estimation along with specific policy ideas to improve evacuation outcomes.

9.6.1) Methodological Recommendations

Considering the study limitations, we first provide several improvements for future papers using RP survey methodology for RUM and RRM estimation. While the general methodology as described earlier should remain, potential improvements include:

- Reducing the number of attributes to reduce considered choice opt-out and attribute opt-out;
- Removing some considered choice sections for choices that did not exhibit strong regret-minimizing behavior or significant variation between attribute levels; and
- Inserting a "choice-blind" SP experiment section in the survey across choices, which more easily reconstructs choice sets, reduces considered choices and attribute-level opt-out, increases attribute level variation, and collects additional samples from an individual.

Of these recommendations, the most drastic is developing an SP survey. While we acknowledge that SP surveys are not well-suited for unrealistic situations, we also realize that RP survey implementation is hard. Moreover, large sample size, increased variation, and opt-out reduction for SP outweigh the limitations. The SP survey could be administered to evacuees by collecting data from individuals who recently made important and difficult evacuation decisions or non-evacuees who are at risk for a specific hazard. While the RP survey collects actual behavior, we recognize that determining the behavioral accuracy of regret minimization may require an SP survey for a hypothetical disaster, particularly to increase the sample size.

9.6.2) Policy Recommendations

In addition to methodological improvements, we offer several policy recommendations for agencies to improve wildfire evacuation outcomes based on our analysis. We focus on significant variables for the RUM models, as we were unable to establish definitive proof of regret across choices. Consequently, we are unable to provide policy recommendations for mode choice. We also note that many of these recommendations are not innovative or surprising. However, we provide them to help build additional consensus of certain strategies for public agencies, which is especially critical for wildfires (as opposed to highly studied hurricanes).

Recommendation: Agencies should encourage evacuees to leave before they visually see the fire. While the precise time to issue mandatory evacuation orders is highly dependent on the fire speed, wind, fuel loads, and geography, agencies should err on the side of caution to ensure that the slowest evacuees is able to leave. Alternatively, agencies could consider advanced trigger models (Li et al. 2019) that identify when officials should issue orders based on the fire and targeted evacuation clearance times.

> Evidence: The departure timing model shows that evacuees chose a departure time when the visual fire was high (significant variable), indicating the importance of environmental cues. An earlier response – leaving when fire visibility is still low – should be encouraged by agencies to reduce later departures, which are riskier.

Recommendation: Agencies should increase evacuation information at the neighborhood level to leverage neighbor networks. Accurate evacuation information, particularly on planned departure times for a time-phased evacuation, should be distributed at a local level through different mechanisms (e.g., community-based organizations, Community Emergency Response Teams [CERTs], neighborhood associations).

> Evidence: Evacuees were more likely to choose a specific departure time, if they experienced pressure from neighbors to leave (significant variable). Neighbors can play a beneficial role in providing useful information or negatively impact the evacuation by propagating rumors.

Recommendation: Agencies should provide clear routing information, including routes not overtaken by fire, to reduce route uncertainty. This may require coordination with other jurisdictions and routing applications (e.g., Waze, Google Maps) to dynamically route around blocked routes (e.g., due to debris). Moreover, agencies need to leverage low-tech forms of communication (e.g., radios), if power is lost or mobile phones do not have coverage.

> Evidence: The departure time model shows that individuals were less likely to choose a departure time, if they were uncertain about their escape route (significant variable). This hesitation may cause more late departures, which places evacuees in higher danger. Moreover, the route choice model shows that people preferred routes with less fire danger (significant variable).

Recommendation: Agencies should prepare transportation operations at a highly localized level (as opposed to a multi-jurisdictional level) to reduce congestion. For example, agencies could implement signal priority, parking restrictions, and/or contraflow at critical intersections or along heavily used road links close to the wildfire impact area.

> Evidence: Evacuees preferred routes that were short-distance (significant variable), and approximately two-thirds of evacuations occurred within the county (see Table 3). These results suggest that most evacuees preferred to remain close by but still outside of the evacuation zone. Naturally, this could lead to notable congestion in neighborhoods.

Recommendation: Agencies should pre-plan public shelters in areas with a low likelihood of fire danger (fire safety), ensure shelters are secure for all populations (personal safety), and provide necessary health supplies and resources (life safety). Since it is uncertain what areas and accommodations will be viable during a wildfire, agencies should establish a safe option for evacuees via public shelters.

> Evidence: Evacuees chose shelters that were more likely to secure safety (significant variable). While the type of safety (e.g., fire, personal, life) could not be determined, the shelter choice model suggests that an improvement in safety (for example, a public shelter) would make it a more attractive option for evacuees (in contrast to more expensive hotels/motels).

9.7) Conclusions

In this paper, we developed a RP survey methodology to estimate both RUM and RRM models. We applied this methodology to a wildfire evacuation choice context that we hypothesized would exhibit regret-minimizing behavior, as opposed to traditional utility-maximizing behavior. Across multiple evacuation choices, we did not find support for this hypothesis, although weak and modest regret-aversion behavior was found for several specific attributes. We also found a class of weakly regret-averse behaviors for route and mode choice. Across all choices, the CRRM model had a poorer fit than the RUM model, which was confirmed by the μRRM model which revealed no or only modest regret aversion. We hypothesize that these results are largely due to poor attribute-level variation in the dataset.

Despite these results, future work on decision rules and evacuations should continue. Indeed, RRM models are heavily dependent on the choice set construction and the dataset. Future work should incorporate the methodological improvements to the RP survey for other disasters, including those beyond wildfires. Moreover, the RP survey methodology can be reproduced beyond the evacuation context (or even transportation context) to other choice situations. Due to limited attribute variation and RP weaknesses, we also recommend testing a SP survey with experienced evacuees and non-evacuees to identify possible regret. We conclude that further exploration of the RP survey methodology and regret testing, using both RP and SP, is needed before an adequate conclusion can reached for using the regret-minimizing tool for evacuation behavior.

9.8) Acknowledgements

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9.9) Appendix

9.9.1) Mixed-Decision Latent Class Choice Model (MDLCCM) Overview

While the CRRM and μRRM models assume that all respondents make decisions using the same decision rule, the MDLCCM allows for additional heterogeneity through the mixing of decision rules. This mixing is allowed through a latent class choice model (LCCM) as developed in Hess et al. (2012). Since an individual's decision rule is not observed, an LCCM is an intuitive method for representing mixtures of decision rules. In this model, individuals may belong to a class based on whether their decision rule is regret-based or utility-based. As explained in Hess et al. (2012), the difference across classes is a result of both different parameters and the assumed behavioral process. We first mention that choice probabilities for a choice y_i for utility or regret is now conditional on whether the individual belongs to a regret (r) or utility (u) class:

$$P(y_i|r) = \frac{\exp(-R_i)}{\sum_{j=1\ldots J} \exp(-R_j)} \tag{7}$$

$$P(y_i|u) = \frac{\exp\,(V_i)}{\sum_{j=1\ldots J} \exp(V_j)} \tag{8}$$

In the utility equation, V_i is the associated utility for alternative i. To account for the different decision rules and parameterizations associated with the regret- and utility-class, the probabilities for belonging to each class (expressed as π) are multiplied by the choice probability for the alternative under a given choice model.

$$P(y_i) = \pi_r P(y_i|r) + \pi_u P(y_i|u) \tag{9}$$

One item to mention is that we focus entirely on the class-specific model formulation. A clear extension of this is to develop a membership model, which could e.g. include socio-demographic and context-related factors. In addition, while this type of mixture-decision model works best with panel data (i.e., where the same respondent makes multiple choices), its use for a single choice remains viable.

9.9.2) Appendix Tables

Table A1: Construction of Choice Sets for Survey for Revealed Preference and Considered Alternatives

Choice	RP Alternatives		Considered Alternatives
Departure Timing	<u>Date Options</u> Monday, Dec. 4 Tuesday, Dec. 5 Wednesday, Dec. 6 Thursday, Dec. 7 Friday, Dec. 8 Saturday, Dec. 9 Sunday, Dec. 10 Monday, Dec. 11 Tuesday, Dec. 12 Wednesday, Dec. 13 Thursday, Dec. 14 Friday, Dec. 15 Saturday, Dec. 16 Sunday, Dec. 17 Monday, Dec. 18 Tuesday, Dec. 19 Wednesday, Dec. 20	<u>Time of Day Options</u> 12:00 AM 1:00 AM 2:00 AM 3:00 AM 4:00 AM 5:00 AM 6:00 AM 7:00 AM 8:00 AM 9:00 AM 10:00 AM 11:00 AM 12:00 PM 1:00 PM 2:00 PM 3:00 PM	<u>Amount of Time Before or After Chosen Alternative</u> More than 1 day earlier 1 day earlier 12 hours earlier 6 hours earlier 3 hours earlier 1 hour earlier Less than 1 hour earlier Less than 1 hour later 1 hour later 3 hours later 6 hours later 12 hours later 1 day later More than 1 day later

<table>
<tr><td></td><td>Thursday, Dec. 21
Friday, Dec. 22
Saturday, Dec. 23
Sunday, Dec. 24
After Sunday, Dec. 24</td><td>4:00 PM
5:00 PM
6:00 PM
7:00 PM
8:00 PM
9:00 PM
10:00 PM
11:00 PM</td><td></td></tr>
<tr><td>Route</td><td colspan="2"><u>Route Options</u>
Fill-in of main roads in order
(e.g., Spruce Drive, Harrison Parkway, Highway 101, Interstate 405)</td><td><u>Route Options</u>
Fill-in of main roads in order
(e.g., Spruce Drive, Harrison Parkway, Highway 101, Interstate 405)</td></tr>
<tr><td>Mode</td><td colspan="2"><u>Mode Options</u>
One personal vehicle
Two personal vehicles
More than two personal vehicles
Carpool/vanpool with non-household
Shuttle service
Ridesourcing/TNC (e.g., Uber, Lyft)
Microtransit (e.g., Via)
Carsharing (e.g., Zipcar, GIG Car Share)
Rental car
Rail (e.g., light/heavy, subway/metro, trolley)
Bus
Walk
Motorcycle/scooter
Bicycle
Aircraft
Recreational vehicle (RV)
Other</td><td><u>Mode Options</u>
One personal vehicle
Two personal vehicles
More than two personal vehicles
Carpool/vanpool with non-household
Shuttle service
Ridesourcing/TNC (e.g., Uber, Lyft)
Microtransit (e.g., Via)
Carsharing (e.g., Zipcar, GIG Car Share)
Rental car
Rail (e.g., light/heavy, subway/metro, trolley)
Bus
Walk
Motorcycle/scooter
Bicycle
Aircraft
Recreational vehicle (RV)
Other</td></tr>
<tr><td>Shelter Type</td><td colspan="2"><u>Shelter Options</u>
A friend's residence
A family member's residence
A hotel or motel
A second residence
A public shelter
Any shelter found through a peer-to-peer service (e.g., Airbnb)
A portable vehicle (e.g., automobile, camper, RV)
Other</td><td><u>Shelter Options</u>
A friend's residence
A family member's residence
A hotel or motel
A second residence
A public shelter
Any shelter found through a peer-to-peer service (e.g., Airbnb)
A portable vehicle (e.g., automobile, camper, RV)
Other</td></tr>
<tr><td>Reentry</td><td colspan="2"><u>Reentry Options</u>
Any date after and including Dec. 4</td><td><u>Amount of Time Before or After Chosen Alternative</u>
More than 7 days earlier
5-7 days earlier
3-4 days earlier
2 days earlier
1 day earlier</td></tr>
</table>

		Less than 1 day earlier Less than 1 day later 1 day later 2 days later 3-4 days later 5-7 days later More than 7 days later

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Chapter 10: Conclusions and Research Directions

10.1) Dissertation Conclusions

This dissertation explored three important and understudied topics in evacuations – the sharing economy, (joint) choice modeling, and regret minimization – to determine opportunities and recommendations that could improve three critical challenges:

1) Increasing evacuation compliance to mandatory evacuation orders;
2) Improving transportation responses in evacuations to reduce congestion, evacuation clearance times, and evacuee risk; and
3) Ensuring all populations, especially those most vulnerable, have transportation and shelter.

To explore these topics and challenges, I collected survey data from individuals impacted by three disasters:

- 2017 Hurricane Irma in Florida (n=645);
- 2017 December Southern California Wildfires (n=226); and
- 2018 Carr Wildfire in California (n=284).

In addition to these surveys, I led four focus group discussions with vulnerable populations (n=37) and conducted interviews with high-ranking emergency management experts (n=24) to assess the social equity implications and feasibility of the sharing economy in disasters, respectively.

Each dissertation chapter presents a unique understanding through empirical evidence on how to improve evacuation outcomes related to compliance, congestion, and/or social equity. With its theoretical and methodological contributions across all three topic areas, this dissertation takes an important step in broadening evacuation research to consider other pathways to improve transportation outcomes. As with all explorations, refinement will be necessary. Equally important, work is needed to bring together research and practice such that preparedness for, response to, and recovery from disasters and other emergencies is data driven, not just a function of tradition and rules of thumb. To begin this process, I developed several high-level takeaways derived from this dissertation.

1) The sharing economy can be a viable mechanism to support evacuations and supplement public resources. Whether through peer-to-peer or business-to-peer sharing, an opportunity exists in capacity, feasibility, and willingness. However, any future mechanisms should: 1) consider partnerships with sharing economy companies currently working in disasters; 2) leverage social capital (e.g., trust and compassion); and 3) prioritize vulnerable populations to ensure that the sharing economy achieves higher compliance in evacuations and increased social equity. Even though the sharing economy may only help a fraction of evacuees, the safety and quality of life benefits are substantial, especially for those who most need resources.

2) Choice making in evacuations is highly complex and is driven by multiple factors related to risk perceptions, demographic variables, household characteristics, communication mechanisms, and unobservable variables. However, there is considerable variability in the relative effect and direction of variables, lacking consistency across hazards and events. Moreover, choices in evacuations are correlated and should be considered jointly. Further work is necessary to determine if these choices are just correlated or exhibit a stronger joint structure such as sequencing or

hierarchy. Regardless, joint effects and correlated structures indicate that thoughtful compliance and congestion strategies for evacuations can be effective and targeted to specific groups of people, locations, and time points. Moreover, attributes of evacuation alternatives affected choice making, further indicating how perceptions of alternatives drive individual protective actions.

3) Regret minimization as a decision rule was not more accurate in predicting or describing evacuee behavior than utility maximization. This negative result comes with caveats, as some models indicated the potential for regret minimization. Moreover, a single revealed preference dataset does not provide any conclusive results, and adjustments to the methodology could yield different conclusions. This area of research requires significantly more exploration to determine how regret theory can improve evacuation outcomes related to compliance, congestion, and social equity.

In addition to these high-level takeaways, I provide more specific conclusions from the dissertation chapters in the following sections to tackle three critical challenges – compliance, congestion, and social equity – in evacuations. Each conclusion also contains several of the most salient recommendations that should be implemented at mostly local and regional levels of governance. Some conclusions and recommendations are taken directly from the previous chapters, while others have been modified to combine results from multiple chapters. It should be noted that some recommendations, particularly those related to choice modeling results, are not innovative or new. Nevertheless, the recommendations are driven by empirical evidence, reaffirm prior evacuation work, and/or contain additional behavioral nuances that may nudge choice making. Following these recommendations, I provide a series of research directions and remaining gaps that I discovered through conducting this dissertation. I identified important research needs related to: 1) empirical data, 2) choice modeling, 3) innovative mobility strategies, 4) resilience and sustainability, and 5) public safety power shutoffs. Altogether, this concluding chapter represents the culmination of the dissertation and discoveries made during the doctoral journey.

10.2) The Sharing Economy in Evacuations

10.2.1) Limitations of the Sharing Economy

<u>Conclusion: To be successful in a disaster, a sharing economy strategy must address key concerns related to safety, social equity, communication, and driver reliability.</u>

Expert interviews exposed 13 critical limitations to employing the sharing economy in disasters. Key limitations included: 1) ensuring that drivers/hosts are available; 2) determining who pays for the resources; 3) overcoming the digital divide; and 4) reducing the impact of vehicles on congestion. Experts also expressed concern over failing to match drivers with riders due to communication issues, overloading the wireless network, and determining liability and training requirements. Several experts were strongly opposed to the sharing economy as a general evacuation strategy and were mostly concerned about pre-disaster planning and communication infrastructure required to properly distribute shared resources in a disaster. These issues were discussed within the context of a lack of sufficient resources (i.e., time, money) to develop partnerships. They also expressed distrust for private companies to act benevolently during the disaster. Questions also remain in the structure and mechanics of any future partnerships in evacuations. Several additional concerns for the sharing economy include: 1) a lack of sharing economy resources in some geographies; 2) varying coordination needs between agencies and companies; 3) high dependency on communication and technology; and 4) the inability of some vulnerable groups to access and use shared resources due to cost, physical or mental ability, discrimination, structural racism, and/or communication. Shared resources should not be a primary strategy for evacuating or sheltering residents, but a tool in the response toolkit. Most evacuations will continue to be dominated by personal automobiles and sheltering in family/peer residences. Moreover, companies may go out of business and be unable to fulfill trips or shelter matching. However, shared resources – whether provided by companies, public transit agencies, or private citizens – can still play a role in providing help to a small proportion of evacuees, particularly those with the greatest need.

> Recommendation: To combat catastrophic event limitations, significant planning is necessary. For a community-based approach, individuals will need to identify carless neighbors before an event, and community organizations will need to match members and evacuees in advance. At public shelters, transportation sharing may require physical carpooling boards for trips to stores and health appointments. Sheltering will also require planning in advance through neighbors or community organizations. A similar approach is needed for private companies, with preformulated plans on where to send drivers and how to contact potential hosts.

> Recommendation: Agencies should consider addressing some limitations by developing memoranda of understanding (MOU). This mechanism creates informal partnerships between levels of government, public transit agencies, and companies, beginning first with information sharing and situational awareness. The document provides an agreed upon framework that sets general expectations and communication mechanisms in a disaster. MOUs could also contain guidelines and procedures for surge flagging, reimbursement schemes, and liability.

> Recommendation: To improve equitable outcomes and overcome the digital divide (i.e., inability to use technology and/or the Internet), agencies and companies should consider developing low-tech solutions that could operate in a disaster, including options to call for rides and shelters, rather than solely offering a smartphone app. Strategies may also require person-to-person contact or physical bulletin boards, such as those formally used for carpool matching.

> Recommendation: Public transit agencies should build evacuation plans that provide routing, pickup, and drop-off information to evacuees. Agencies will need safeguards in place to ensure that drivers are trained and show up during the disaster. Moreover, agencies with their own microtransit, ridehailing/transportation network companies (TNCs), or carsharing fleets could provide reliable service to evacuees. Agencies without these systems should consider developing their own fleets to be used under normal and disaster conditions. All public transit agencies should work with companies to determine appropriate evacuee drop-off points that connect to public transit.

10.2.2) Benefits of the Sharing Economy

Conclusion: The sharing economy could constitute an additional and innovative tool for evacuations that could solve some issues including: resource deficiency, slow responsiveness, poor communication, and low support for vulnerable groups.

Interviews with 24 high-ranking experts (including six directors/executives of emergency/transportation agencies, two executives of sharing economy companies, and eight senior-level agency leaders) yielded 11 key sharing economy benefits in disasters. Benefits for local agencies included: 1) added resources to move or shelter individuals; 2) redundant resources; 3) a more flexible and adaptive resource pool; 4) support of vulnerable population; 5) information gathering; and 6) an additional communication method to the public. Sharing economy companies could also benefit through: 1) positive press coverage; 2) improved business continuity; 3) asset removal and protection; 4) a more amenable regulatory environment from building goodwill; and 5) stronger connections with local communities. These benefits dovetail with expert opinions on specific transportation and non-transportation actions that could improve response. For transportation response, experts suggested that pickups at individual homes would increase accessibility. For example, direct pickups could specifically assist vulnerable populations. Drop-off points could be established at public transit stops or public evacuation shelters. Apart from transportation response, experts suggested focusing on communication and situational awareness. For example, sharing economy platforms, particularly on smartphones, could serve as a communication tool for connecting with drivers and passengers through push notifications or within-app notifications.

> Recommendation: Agencies should consider developing TNC pilot programs that test the feasibility of sharing economy partnerships through first- and last-mile connections, paratransit supplements, and/or driver retention mechanisms to ensure an adequate supply of drivers and vehicles in a disaster.

> Recommendation: Partnerships and pilot programs should first be tested during the recovery period when risks from the hazard are lower. Transportation response and situational awareness would be more feasible during this time period. Future sharing strategies should expand first into the pre-disaster period (particularly for disasters with enough notice time) and then during the disaster when risks to drivers are highest.

10.2.3) Recent Sharing Economy Actions

Conclusion: Sharing economy companies are acting in disasters, and these actions have become more consistent and structured.

Since Hurricane Sandy in 2012, sharing economy companies (e.g., Airbnb, Lyft, Uber) have acted in at least 30 disasters in the United States. Early actions by companies were largely ad-hoc, as Airbnb hosts offered free housing through a peer-led movement, and TNCs attempted to cap surge pricing and suspend service. These companies soon began to develop more structured actions. Airbnb created its Disaster Response Program to provide free housing; Lyft developed the Round Up and Donate Program and Relief Rides to raise money and offer ride credits; and Uber pledged specific dollar amounts for rides, food, and relief. Since 2018, all three companies have acted in disasters regularly with more systematic policies. Airbnb continues to offer housing for free to evacuees through its new Open Homes Program. Lyft rebranded its program, now called Wheel for All, expanding ride credits to disadvantaged individuals. Uber developed the Global Security Center, which now handles most disaster actions.

> Recommendation: Agencies should create partnerships with sharing economy companies, particularly in larger cities where these companies maintain a high presence. Sharing economy companies have an extensive network of assets that can be leveraged quickly. However, asset availability depends on the willingness of drivers/hosts to participate. Partnerships also require substantial planning, and some people may not trust companies to help in disasters.

> Recommendation: Agencies should consider communicating with sharing economy companies through stakeholder engagement meetings, alliance development (through non-governmental organizations), and/or training exercises to improve relationships with companies. These actions will begin the process of information sharing, which could become invaluable in a disaster.

> Recommendation: Agencies should develop a system that flags surge pricing (i.e., rapid increases in TNC costs) to increase agency oversight of price gouging violations. This mechanism would mirror regulations for other goods and resources in a disaster.

10.2.4) Sharing Reservations

Conclusion: Private citizens, for both hurricanes and wildfires, had a number of reservations and concerns about sharing resources in an evacuation.

Hurricane respondents (Hurricane Irma survey) tended to have more reservations related to sheltering than transportation. Safety/security was the top reservation for both resources, with 74.1% stating concerns for sheltering and 57.9% for transportation. The value for sheltering is likely due to the personal nature of hosting an evacuee at one's home. Feeling responsible for the individual(s) was also a major concern (60.9% for sheltering and 47.3% for transportation), along with having to interact with a stranger (51.6% and 40.8%). Approximately 54% were also concerned about having enough space for passenger(s) belongings in the case of transportation. For wildfires (Southern California Wildfires and Carr Wildfire surveys), sheltering concerns included uncertainty about one's own safety and security (55.3% to 57.4%), feeling responsible for additional house guests (45.1% to 48.7%), disruption to everyday tasks (37.3% to 42.0%), and having to interact with a stranger (35.9% to 40.7%). For transportation, safety and security was still a major concern (44.6% to 48.4%), but respondents were also highly worried about not having enough vehicle space for the additional passenger(s) belongings (42.9% to 53.7%) and adding extra time to the evacuation (45.7% to 56.6%). A weighted sample aggregation using eight binary logit models from wildfire data also revealed that non-sharers consistently had more concerns than sharers, with the exception of sharing transportation during the evacuation. This exception is influenced by two factors: 1) high predicted choice probabilities for sharers, which influences aggregated probabilities upward and 2) real and substantial concern from sharers about this scenario.

Recommendation: Agencies could potentially minimize safety concerns by matching providers and evacuees through established community-based organizations (CBOs). Both providers and users of shared resources may be more comfortable with sharing through established CBOs and volunteer networks. CBO credibility may also increase trust of neighbors and strangers. While local agencies could also match providers and users, CBOs are well positioned to encourage members and other volunteers to share resources. Private sharing companies often partner with CBOs (e.g., Uber and the American Red Cross, Lyft and United Way) to provide rides and shelter in disasters.

Recommendation: Agencies (particularly public transit agencies) and/or private companies should consider setting pickup points for shared transportation along major arterial roadways. With limited time to evacuate and travel to a destination, evacuees exhibited strong risk aversion to increasing the travel time of their evacuation or deviating from their route in order to share transportation. Pickup points could be integrated into a public transit-based response. However, not all individuals will be able to travel to these pickup points, so some vehicles will need to provide point-to-point service to ensure safe and equitable outcomes.

10.2.5) Social Equity Barriers for Vulnerable Groups

Conclusion: Vulnerable groups are highly concerned with driver availability and reliability, the ability of vehicles to reach evacuation zones, costs, and communication challenges. Each group also has specific limitations related to their vulnerability for a shared resource strategy.

Four focus groups (n=37) of vulnerable populations (low-income individuals, older adult, individuals with disabilities, Spanish-speaking individuals) impacted by California wildfires expressed that driver availability and reliability were critical concerns that would hamper a TNC-based sharing strategy. Moreover, they noted that drivers might not go into evacuation zones due to safety concerns, rides might be expensive, and the service would be unavailable to those without smartphones, a bank account, or knowledge of English. By group, older adults were worried that TNCs would add confusion to the evacuation process; individuals with disabilities were concerned about vehicle accessibility; low-income individuals were worried about a lack of driver incentives to assist; and Spanish-speaking individuals did not trust drivers or companies. In general, most participants exhibited mixed or negative reactions to TNCs as a shared resource strategy in evacuations. Despite noting these limitations, participants were also quick to make recommendations for a general TNC strategy. For homesharing, participants were generally more positive and noted fewer limitations. Limitations expressed included: 1) poor accessibility for disabilities; 2) minimal training for hosts; 3) lack of necessary medical equipment; 4) communication challenges without Internet, smartphones, or Spanish translation; and 5) general low trust of hosts and strangers.

Recommendation: Agencies should consider building more robust public transit-based evacuation plans that incorporate the sharing economy first for first-mile, last-mile connections and second for post-disaster transportation. This strategy would provide trips for carless, low-income, and public transit-reliant individuals; promote faster evacuations (in trip time), especially for those physically unable to evacuate quickly; assist in decreasing evacuation congestion, thus improving evacuation times; and increase accessibility during the recovery period. A public transit plan would also improve trust and concerns about reliability.

Recommendation: Agencies should create partnerships with paratransit providers to identify and assist individuals with disabilities. This recommendation would increase the availability of accessible vehicles to allow for spatially broader and faster coverage in an evacuation; help individuals with disabilities trust drivers and resource providers; and ensure that resource providers are properly trained to assist individuals with disabilities.

Recommendation: Agencies should disseminate information about resources (e.g., assistance filing insurance claims, TNC or public transit rides) prior to evacuations and during the reentry phase through both government agencies and CBOs. By planning ahead, this strategy improves long-term economic and health outcomes for impacted evacuees, especially high-risk populations, and improves reentry processes and subsequent access to resources.

10.2.6) Benefits and Limitations of Shared Resources for Vulnerable Groups

<u>Conclusion: While multiple vulnerable groups could gain considerable benefits from shared resources, ten of the 18 identified vulnerable groups experience three or more key challenges to implementation.</u>

Using the Spatial Temporal Economic Physiological Social (STEPS) equity framework and informed by the four vulnerable population focus groups, this dissertation identified 18 vulnerable groups. Each group was assessed based on shared resource opportunities and challenges. Challenges included: 1) difficulty finding resources; 2) difficulty locating vulnerable individuals; 3) a digital divide; 4) increase in costs or price gouging; 5) high liability for providers; 6) likelihood for discrimination; 7) cultural differences; 8) communication issues; and 9) need for provider training. Opportunities included: 1) increase in resources; 2) increase in evacuation compliance; 3) increase in transportation accessibility; 4) decrease in costs; and 5) maintenance of social connections. A sharing economy strategy would be most feasible for vulnerable groups identified as: carless; asset poor; racial and ethnic minorities; older adult; immigrants; Lesbian, Gay, Bisexual, Transgender, Queer, Other Self-Identification (LGBTQ+) individuals; and required workers. While these groups have both sharing challenges and benefits, they tend to have greater access to technology (in particular mobile phones) and more varied incomes. Therefore, they can more easily access sharing economy resources. Other vulnerable groups, including those identified as unbanked (or underbanked), individuals with disabilities, hospital bound, undocumented immigrants, and homeless would face significant barriers to receiving shared resources. For example, undocumented immigrants would be unwilling to interact with government or private companies, while individuals with disabilities may require additional assistance and accessible vehicles and homes. While shared resources could greatly benefit all groups, challenges exist in locating groups and ensuring they can engage with shared platforms (overcoming the digital divide). All 18 identified vulnerable groups have at least one challenge for implementing shared resources, and ten groups have at least three major challenges.

Recommendation: Agencies should consider the unique needs of specific vulnerable groups. Low-income, unbanked, and asset-poor individuals could benefit through developing regulations that keep costs of resources low (i.e., controlling surging) and allow evacuees to pay for resources (if absolutely necessary) through multiple payment methods including cash. Older adults, medically-fragile populations, and individuals with disabilities would benefit from plans that ensure shared shelters and other accommodations have necessary medical equipment (e.g., oxygen tanks, access to dialysis centers) for fire-based health challenges (e.g., smoke inhalation) in addition to medical supplies to treat chronic illnesses (e.g., insulin for people with diabetes).

Recommendation: Agencies should communicate resource information (and evacuation orders) in multiple languages and through multiple channels. This strategy ensures information is understood by non-English speakers, improves the speed of information dissemination in non-English speaking communities and ethnic enclaves, increases trust between non-English speaking communities and public agencies, and opens resource opportunities for more people.

Recommendation: Agencies should also remove barriers to sharing by: 1) increasing credentialing of drivers and hosts for both companies and private providers; 2) offering training through CERTs or other organizations on how to properly assist others in evacuations; and 3) working with neighborhood associations to develop localized community-based plans to ensure transportation for neighbors.

Recommendation: Agencies should include all vulnerable groups in the planning process for emergency evacuations. This community-based needs assessment allows the input of vulnerable groups in evacuation plans, increases equitable outcomes for those groups, and identifies resources that may be useful for a variety of vulnerable groups.

Recommendation: Local, regional, state, and federal governments should substantively address structural racism and discrimination through stronger laws and policies that ensure all people receive assistance, prioritizing resources and recovery supplies to vulnerable populations. This might include: 1) mandating public transit-based evacuation plans to help carless and mobility-poor populations; 2) requiring all jurisdictions to develop evacuation plans and strategies to increase social equity; 3) ensuring that homeowners and salaried employees are not prioritized over renters and wage earners; 4) requiring evacuation orders and disaster aid information be distributed in multiple languages; and 5) increasing mitigation and preparedness funding for communities with higher proportions of vulnerable populations.

10.2.7) Willingness to Share and Resource Capacity

<u>Conclusion: Even though the sharing economy is currently not highly used in hurricanes or wildfires, private citizens are somewhat willing to share their homes but much more willing to share transportation. Moreover, capacity exists in the form of spare beds and spare seatbelts, indicating potential for sharing.</u>

In a survey of individuals impacted by Hurricane Irma (n=645), only about 1% of respondents used TNCs for evacuation or reentry, and about 5% used homesharing (e.g., Airbnb, VRBO). Surveys conducted of individuals impacted by the 2017 December Southern California Wildfires (n=226) and the 2018 Carr Wildfire (n=284) showed even less sharing use. Despite this low usage, respondents were more willing to offer their own resources. For Hurricane Irma, while only 6.7% were extremely likely to offer shelter to an evacuee at a cost, a larger proportion (19.2%) was extremely willing to provide shelter to an evacuee for free. For transportation, 29.1% of respondents were extremely willing to share transportation before a hurricane evacuation, and 23.6% were extremely willing to share during the evacuation. Wildfire evacuees were generally more willing to share resources. Extreme likelihood to share sheltering for a cost ranged from 11.5% to 14.1%, while extreme likelihood to share sheltering for free ranged from 24.3% to 29.6%. Extreme willingness to share transportation prior to the evacuation was between 36.6% and 48.4%, and extreme willingness to share during the evacuation jumped to between 58.9% and 72.0%. Despite these positive numbers, a significant number of respondents for the hurricane and wildfires were also extremely unlikely to share sheltering or transportation (ranging from 16.0% to 37.2% for the hurricane and 3.1% to 27.0% for wildfires, depending on scenario), suggesting a "ceiling" on willingness to share resources. Regarding capacity, 77% of respondents stated they had two or more spare seatbelts, and only 16.0% had no spare beds/mattresses at home. For the wildfires, between 10.5% and 16.3% did not have spare beds. In addition, among households that evacuated for the wildfires, between 64.0% and 68.5% had at least two empty seats with seatbelts. The availability of resources indicates that vehicles and homes are being underutilized in an evacuation.

> Recommendation: Agencies should bolster neighborhood and community networks as a mechanism for sharing resources by considering community-based outreach. This could be achieved through an information campaign directly from agencies to assist neighbors or collaboration with CBOs to provide more specific and targeted information. This strategy is recommended for all communities, particularly smaller localities without the presence of sharing economy companies.

> Recommendation: Mechanisms and strategies via a resident-based approach should also consider more formalized training by integrating information about how to share resources in disasters into Community Emergency Response Teams (CERTs), if these teams exist. Jurisdictions without CERTs should consider forming these groups to leverage social connections already present in the community. More formalized strategies, such as transferring responsibilities from local governments to CBOs or creating a Shared Resource Reserve Team (operating similar to CERTs) will require significant pre-planning and contacts.

10.2.8) Effect of Trust and Compassion on Sharing

<u>Conclusion: Trust and compassion strongly increase willingness to share resources across all resources for wildfire evacuations.</u>

Four binary logit models using wildfire data from the 2017 December Southern California Wildfires (n=226) and the 2018 Carr Wildfire (n=284) presented results that variables related to high trust and compassion are associated with a higher willingness to share resources. In particular, trust of strangers and neighbors as well as non-selfish compassion (i.e., engaging in activities to help strangers before self-serving activities) and tender compassion (i.e., emotionally-based caring feelings for strangers in need) were especially influential. A brief sample enumeration for likelihood to share was also conducted to transform all trust and compassion variables into zeros (i.e., no respondents have high trust or compassion) and ones (i.e., all respondents have high trust or compassion). This enumeration was meant to find the difference between a high trust/compassion community and low trust/compassion community and quantify the effects of these variables on willingness to share. A significant range existed between a low trust/compassion population and a high trust/compassion population (between 30% and 55% difference depending on scenario). This suggests that very low trust/compassion communities and very high trust/compassion communities will have significantly different likelihoods (leading to eventual actions) to share. Additional strategies may need to be implemented in low trust/compassion communities, especially as social capital is a determinant of disaster recovery success.

> Recommendation: Agencies should work to increase community trust and compassion as part of disaster preparedness to increase willingness to share resources. Strategies might include building community cohesion through: 1) civic pride (e.g., identity, slogans, flags, campaigns), 2) easy-to-replicate neighborhood networks (e.g., phone trees, neighborhood associations), 3) social neighborhood events (e.g., block parties), preparedness events (e.g., community meetings), and 4) disaster-specific neighborhood groups (e.g., CERTs).

> Recommendation: Additional strategies to increase trust and compassion may require monetary assistance or specialty training. Support could come from monetary grants or training by local fire marshals, chiefs, and fire boards with emergency expertise. Developing preparedness guidebooks and brochures would help increase both preparedness and willingness to share, especially if the materials include information on how to share. Agencies should also consider training leaders within neighborhoods on how to connect sharing providers and users. Trustworthy and compassionate leaders and providers are likely rooted in the community and/or have strong social connections.

10.2.9) Factors Influencing Willingness to Share

<u>Conclusion: Past disaster volunteers and community organization members are more willing to share resources, and evacuation urgency helps trigger a sharing response.</u>

Four binary logit models using wildfire data from the 2017 December Southern California Wildfires (n=226) and the 2018 Carr Wildfire (n=284) presented results that past volunteers in disasters were moderately more likely to share for several sharing scenarios. Members of a local community organization or group (e.g., arts/cultural, education/school/PTA, professional/trade, religious, social service/charitable) were also typically more likely to share for several sharing scenarios. Overall, volunteerism was high for these wildfires, as 44.2% (Southern California Wildfires) and 46.8% (Carr Wildfire) volunteered. Moreover, volunteerism for the wildfires increased by 7.5% (Southern California Wildfires) and 13.3% (Carr Wildfire) compared to past volunteerism in a disaster. Several urgency variables for departure timing and routing (e.g., high visual fire level, high smoke level, high traffic levels, and low visibility) increased likelihood to share for some transportation scenarios. Evacuees may realize that some neighbors need significant help and would perish without receiving transportation assistance, indicating that sharing behavior is triggered by the urgency of disasters.

> Recommendation: Agencies should ensure that community members, including evacuees, are able to easily volunteer (e.g., developing volunteering groups, fast signup), which will

help to increase the amount of resources available for all temporal points in the disaster. Agencies may also need to maintain a volunteer network, including information about past volunteers, to ensure that volunteerism remains high for the next disaster. For example, agencies could reward assistance through volunteer recognition, communicate with volunteers on a regular basis, and/or host social gatherings for volunteers.

Recommendation: Agencies should develop stronger relationships and partnerships with CBOs and other community groups, especially those with a strong volunteer and supply network. This flexible network could be called upon quickly during a disaster to provide transportation and sheltering to those who need it most. Volunteers through CBOs and community groups may also be viewed as more trustworthy. Agencies should also work to expand the networks of larger NGOs (e.g., American Red Cross) and churches, which may be able gather resources from a larger geographical area.

10.3) (Joint) Choice Making in Evacuations

10.3.1) Correlation of Sharing Behavior

<u>Conclusion: Sharing behavior across hypothetical sharing scenarios is correlated and linked via classes of individuals and/or joint behavioral preferences.</u>

From the Hurricane Irma survey data, three types of models were developed – four binary logit models, one portfolio choice model, and a multi-choice latent class choice model (LCCM). The multi-choice LCCM captures conditional independency (i.e., correlation) between choices; segments individuals into distinct latent classes; and links choices through a class membership model of demographic characteristics. While the binary logit models capture in detail the variables that affect each separate scenario, cross-tabulations of the four scenarios indicate significant correlation in willingness to share. The multi-choice LCCM found three classes: 1) adverse sharers (i.e., individuals strongly unwilling to share for any scenario), 2) interested sharers (individuals moderately willing to share for any scenario), and 3) transportation-only sharers (i.e., individuals willing to share transportation only). Each class had different likelihoods to share across the four scenarios and were composed of different demographics, indicating the presence of unique provider groups. The portfolio choice model (PCM), which captures joint preferences (if present) between primary choice dimensions (i.e., the sharing scenarios), showed similar joint preferences, particularly between the transportation scenarios and between the sheltering scenarios. Some overlap of the demographic variables that influenced willingness to share existed between the binary logit and PCM models, but these results were largely inconclusive.

Recommendation: A transportation sharing strategy should not be constrained temporally and should allow individuals to share before, during, and after the disaster. Agencies will need multiple communication mechanisms (e.g., mobile phones, Internet, landlines, neighborhood networks) to ensure that those in need of rides can be properly matched with providers. Agencies will also need to ensure that drivers are safe and do not enter a hazardous area.

Recommendation: A sheltering sharing strategy should be free for evacuees. This may place a small administrative cost on the agency or company running the matching algorithm. Similar to transportation, agencies will need multiple communication mechanisms (e.g., mobile phones, Internet, landlines, neighborhood networks) to properly match users and providers.

Recommendation: Agencies should consider combining a transportation strategy and a sheltering strategy into a holistic program. The program should be constructed and advertised as an evacuee assistance program that offers multiple opportunities for people to volunteer and assist.

10.3.2) Influencers of (Joint) Sharing Behavior

Conclusion: Most demographic variables (except for families and homesharing users) were weak and sporadic indicators of sharing, further suggesting the role of trust, compassion, and social networks in influencing sharing behavior.

Across the Hurricane Irma binary logit, multi-choice LCCM and PCM models for willingness to share, there was substantial variation on which demographic variables were important factors, along with their direction of influence. This indicates that other variables, including those related to social capital such as trust, compassion, and social networks, may be stronger drivers of sharing behavior. However, several variables did have some influence on willingness to share. First, families were unwilling to share across scenarios, indicating likely concerns about their children's safety and security. Across models, spare capacity (i.e., seats with seatbelts, spare beds) was positive but mostly insignificant in increasing sharing. The results suggest a minimal role of spare capacity as a motivator for sharing. Income had an uneven influence on the willingness to share, as there was no clear directionality of influence. The results again indicate that other demographics (including those related to trust and compassion) are more important for willingness to share. Finally, homesharing users (e.g., Airbnb, VRBO) 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.

Recommendation: Agencies should first focus on outreach to households without children in a sharing strategy. Outreach about an evacuation assistance program could be conducted via an online or mailing campaign. Other characteristics of the household (i.e., income, residence structure type, age of members) should not be considered for targeted outreach.

Recommendation: Agencies should partner with and leverage existing homesharing platforms (e.g., Airbnb, VRBO) to increase willingness to share sheltering. Both hosts and users of homesharing should be encouraged to provide shelter to evacuees. While the current Airbnb Open Homes Program only encourages hosts to provide shelter, a future sheltering strategy should also contact and encourage regular or long-time users of homesharing. These individuals likely understand the homesharing process and would use this experience to help others in a disaster.

10.3.3) Correlation of Hurricane Evacuation Choices

Conclusion: Choices in hurricane evacuations are correlated and should be modeled jointly to account for this correlation and develop more nuanced evacuation strategies.

From the Hurricane Irma survey data, a PCM was developed using the primary choices an evacuee must make after deciding to evacuate (i.e., departure day, departure time of day, destination, shelter type, transportation mode, and route). Traditionally, these decisions are analyzed in isolation, but cross-tabulations indicated significant correlation between decisions. As mentioned previously, the PCM captures decision-dimensional dependency (if present) without requiring choices to be correlated or sequential. Put another way, a PCM reframes the choice set as a bundle of concurrent decision dimensions, allowing for flexible and simple parameter estimation. Joint preferences were found for evacuating early (i.e. more than three days before landfall and: 1) at night (i.e., between 6:00 p.m. and 5:59 a.m.) and 2) on highways (used highways for majority of route). Joint preferences were also found for evacuations at a regular time (i.e., between 2-3 days before landfall) and on highways; within county evacuations and using two or more vehicles; and within Florida evacuations and using two or more vehicles. Joint dislikes were found for early and within Florida evacuations; within county and highway evacuations; within Florida evacuations and private shelters (i.e., friend's or family's residence); and within Florida and highway evacuations. A joint dislike was also found for nighttime evacuations and both within Florida evacuations and within county evacuations.

> Recommendation: Agencies should ensure that there are adequate resources to manage significant nighttime traffic along highways well before hurricane landfall. This may include pre-placing static resources (i.e., cones) or deploying dynamic resources (i.e., traffic coordinators). Transportation operations including signal priority, shoulder-running, and contraflow may also need to be prepared for these evacuations. A public transit-based plan should also consider nighttime evacuations, but with routing on major arterials (i.e., not a highway) to reduce congestion on highways. Finally, supplies including food, water, and gas will need to be available for these evacuees. Agencies should also be prepared for significant long-distance nighttime traffic by improving interstate communication and resource placement.

> Recommendation: Agencies should deploy traffic management resources locally to handle significant multiple-vehicle evacuations that occur within county. Signal priority may be the most effective transportation response for these shorter distance evacuations. Agencies may also consider leveraging the unused capacity of these extra vehicles as a shared transportation response. Agencies should also deploy resources for public transit, traffic, and public shelters for medium- and short-distance evacuees much earlier (at least three days before landfall).

10.3.4) Factors Influencing Decision to Evacuate or Stay in Hurricane Evacuations

<u>Conclusion: The decision to evacuate or stay in a hurricane is strongly driven by risk perceptions and mandatory evacuation orders, which separately influence the composition of two clear evacuation classes.</u>

From the Hurricane Irma survey data, a LCCM was constructed to identify population segments with distinct behavior related to the decision to evacuate or stay. Two clear classes were found: 1) a class of keen evacuees and 2) a class of reluctant evacuees. Keen evacuees preferred to leave and were influenced by strong risk perceptions. However, mandatory evacuation orders were not significant in influencing this group. In other words, this group will leave regardless of whether they receive a mandatory evacuation order. Families and those living in Southwest Florida (where Hurricane Irma made landfall) were more likely to be part of this class. The second class, reluctant evacuees, preferred to stay and were influenced by barriers to evacuating such as worry about finding gas, worry about finding housing, concern over housing costs, and likelihood belief of work requirements. Despite this reluctance, mandatory evacuation orders were powerful motivators to encourage evacuations from this group. Females, previous evacuees, households with pets, and long-time residents (i.e., living more than 10 years in their residence) were more likely to be part of this class.

> Recommendation: To increase compliance rates, agencies should focus orders on previously evacuated hurricane zones and neighborhoods with long-time residents. These individuals tend to be less likely to evacuate but can be influenced by orders. Language in mandatory evacuation orders should also be strengthened to better convey disaster risk.

> Recommendation: Agencies should use mandatory evacuation orders as instruments for reducing concerns over evacuation logistic barriers. For example, agencies should convey sheltering information, including shelters that accept pets, concurrently with mandatory orders. This extra communication should coincide with an increase in public shelters and alternative shelter availability to reduce concerns over finding and paying for housing. Additional information such as available fuel and services should also be provided. Agencies should also consider working with employers to reduce work requirements (particularly for hourly workers) and allow more flexible work arrangements (e.g., telecommuting).

10.3.5) Factors Influencing Decision to Evacuate or Stay in Wildfire Evacuations

<u>Conclusion: The decision to evacuate or stay/defend in wildfires is most influenced by mandatory evacuation orders and risk perceptions with uneven influence from household and individual characteristics.</u>

From the survey data for the 2017 December Southern California Wildfires and 2018 Carr Wildfire, two separate binary logit models were developed for the decision to evacuate or stay/defend. Mandatory evacuation orders were highly significant in increasing the likelihood to evacuate for both wildfires. Risk perception variables (e.g., worry about the speed of the fire, likelihood belief of utility loss, and likelihood belief of injury or death) generally increased evacuations. Interestingly, the belief of structural damage had diverging effects between the wildfires, suggesting that the samples viewed structural damage differently (i.e., a need to defend vs. personal risk from a severe wildfire). Households with pets, homeowners, very low-income households, and previous evacuees were less likely to evacuate for both fires, but the results were mostly insignificant. Long-term residents were less likely to evacuate from one wildfire. Females, families, young adults, older adults, and higher educated individuals were more likely to evacuate for at least one fire. However, variables were largely insignificant. The results suggest that mandatory evacuation orders and risk perceptions are most important in wildfire evacuations, while demographics are less important. Results also indicate that demographic characteristics are not generalizable across geographies and that evacuation rates will vary depending on the community.

Recommendation: Agencies should focus on distributing mandatory evacuation orders quickly and widely to increase evacuations. These orders should contain additional information (e.g., shelters, safe routes) to increase situational awareness. Orders should be distributed across as many communication platforms as possible, including low-tech methods (e.g., sirens, radios), and in multiple languages as needed. Given the speed of wildfires, orders need to be communicated with enough lead time for people to mobilize. This is especially important for vulnerable populations (e.g., older adults, individuals with disabilities, homebound individuals) that will require additional time and/or assistance to evacuate. Agencies should also focus communication efforts in neighborhoods that have more low-income residents, homeowners, previous evacuees, and long-term residents. Low-income residents may also include other vulnerable populations such as unbanked, asset poor, individuals with disabilities, and homebound individuals.

Recommendation: Agencies should prepare additional traffic measures, especially on-ground traffic control by personnel, for areas without power or areas likely to lose power to handle additional congestion. Given the importance of utility loss in encouraging evacuations, low-tech transportation strategies will be needed to ensure safe evacuations (particularly if a power loss impacts traffic lights, streetlights, and cell service). New public safety power shutoff (PSPS) efforts that cut power prior to a fire due to dangerous weather events will make these strategies even more important.

10.3.6) Correlation of Wildfire Evacuation Choices

<u>Conclusion: Similar to hurricanes, choices in wildfire evacuations are correlated and should be modeled jointly to account for this correlation and develop more nuanced evacuation strategies.</u>

Data from the 2017 December Southern California Wildfires and 2018 Carr Wildfire informed two portfolio choice models (PCMs), which permit the estimation of choice dimension dependency (which may or may not exist). In these models, departure day, departure time of day, destination, shelter type, transportation mode, and route were considered together as a bundle of choices. Immediate evacuations (occurring at the height of the wildfires) were jointly preferred with night evacuations (e.g., 6:00 p.m. - 5:59 a.m.), which is a result of the nighttime impact of both fires. For at least one fire, individuals also jointly preferred immediate evacuations with within county evacuations, private shelters (e.g., residence of family or friend), and two or more vehicles. Nighttime and within county evacuations as well as private shelter and within county evacuations were jointly preferred for both fires. However, within county and highway (e.g., majority of route on highway) evacuations were jointly disliked for both fires. Evidence also indicates negative joint preference of immediate and highway evacuations as well as multiple vehicle and highway evacuations. For one fire, private shelter and multiple vehicle evacuations were jointly preferred, but this was somewhat insignificant.

Recommendation: Agencies should prepare for significant localized congestion during nighttime evacuations at the height of the wildfires. Agencies should identify neighborhoods with limited exits where localized congestion is likely to occur. Personnel should be prepared and trained to direct traffic, alter signal timing, and increase capacity (via contraflow and shoulder-running) to handle nighttime traffic in low-visibility conditions. Agencies should also be prepared for significant traffic within counties (rather than cross-county traffic).

Recommendation: State transportation agencies should focus on deploying assets on arterial streets and two-lane state highways during the immediate outbreak of the wildfire before deploying resources on interstates or limited-access highways. However, if fire threatens these assets, state agencies should continue to respond effectively with closures and assets when and where necessary.

10.3.7) Demographic Influence in Wildfire Evacuation Choice Making

Conclusion: While demographic characteristics correlate with wildfire evacuation choices with varying directions and significance, these characteristics still indicate influences that can be used to improve behavioral understanding and evacuation outcomes.

From the same evacuation PCMs for the 2017 December Southern California Wildfires and 2018 Carr Wildfire, demographic variables could be specified for each choice (i.e., any bundle containing that choice dimension). The demographic variables were not consistent across wildfires, which mirrors results found in Section 10.3.5. For departure timing, those with an extreme likelihood belief of injury or death, low-income households, and long-term residents were less likely to evacuate at the height of the Carr Wildfire. For the Southern California Wildfires, older adults and those specifically impacted by the Thomas Fire (one fire within this group of wildfires) were also less likely to evacuate immediately. Previous evacuees (only Southern California Wildfires) and homeowners (both wildfires) were more likely to evacuate at the height of the fires. For time of day, those who received a voluntary evacuation order were less likely to evacuate at night (both wildfires). Those respondents with extreme belief of structural damage and those specifically impacted by the Thomas Fire (Southern California Wildfires), as well as those with extreme belief of injury/death and low-income individuals (Carr Wildfire) were more likely to evacuate at night. Additionally, Carr Wildfire evacuees with a disability and those with a belief that first responders were not going to be available were less likely to evacuate at night. Higher education (Carr Wildfire) and being impacted by the Thomas Fire (Southern California Wildfires) were correlated with evacuating out-of-county. For the Southern California Wildfires, long-time residents were more likely to stay within county. In addition, those with an extreme likelihood belief of injury/death were more likely to stay at a private shelter (e.g., friend/family), while those with work requirements were less likely to do so. Carr Wildfire evacuees with belief of work requirements and older adults were more likely to choose a private shelter, while having a disability and extreme worry about finding housing decreased that likelihood. Evacuees from both wildfires who owned two or more vehicles were more likely to use two or more vehicles in the evacuation. Receiving a mandatory evacuation order and owning a pet (Southern California Wildfires) as well as having children and having a belief of injury/death (Carr Wildfire) increased likelihood to use multiple vehicles. Low-income households (Carr Wildfire) were less likely to use two or more vehicles. Finally, individuals who received a voluntary evacuation order were less likely to use highways for both wildfires. Those who received a mandatory evacuation order (Southern California Wildfires) and homeowners (Carr Wildfire) were less likely to use highways.

Recommendation: Local public transit agencies should have a plan to rapidly respond in a wildfire (i.e., at the height of the fire) to effectively transport evacuees, especially older adults and low-income households. Public transit offers a free option for residents to evacuate, but only if vehicles and drivers are deployed quickly and to pre-identified locations that are publicly known. Pre-planning this response will be necessary.

Recommendation: Agencies should be prepared for substantial evacuations at night for large wildfires and should only use mandatory orders to elicit nighttime evacuations. Agencies should be aware that voluntary evacuation orders are not effective in encouraging people to leave at night.

Recommendation: Agencies should increase personnel and transportation response for congestion in neighborhoods with a high concentration of families, high car ownership, and prior experience with wildfires. Agencies should also deploy congestion-reduction measures in mandatory evacuation areas prior to the communication of orders. Resources will also need to be available for lower-income neighborhoods, including those with a higher renter population that are less likely to evacuate, to ensure equitable outcomes. Community-based organizations could serve as a trusted authority within the community to provide resources.

Recommendation: Agencies should increase road congestion reduction measures on local roads near mandatory evacuation zones while increasing highway measures near voluntary evacuation zones. Voluntary evacuees may have additional time to evacuate, allowing use of highways and thereby reducing congestion closer to the fire danger area.

10.4) Regret Minimization in Evacuations

10.4.1) Effect of Attributes of Alternatives on Wildfire Evacuation Choices

<u>Conclusion: Attributes of departure times and routes are influential in how wildfire evacuees make choices, regardless of the decision rule. Attributes of transportation mode, shelter type, and reentry timing are not powerful indicators of choice, suggesting stronger importance of demographic variables, risk perceptions, and/or resource availability.</u>

Through a revealed preference survey of 2017 December Southern California Wildfire evacuees that reconstructed choice sets and attributes of alternatives, both utility-maximizing and regret-minimizing models were developed for departure timing, route choice, mode choice, shelter choice, and reentry timing. Rather than employing demographics and risk perceptions as factors for evacuation choices (for example in Section 10.3.7), attributes of these choices were explored. For departure timing, both utility- and regret-based models showed that immediate fire danger, pressure of neighbors to leave, uncertainty of escape route, visibility, and visual fire level all influenced when an individual decided to depart (as compared to their other considered departure times). Individuals chose departure times with clearer visibility, higher visual levels of the fire, and more route certainty. Regarding route choice, evacuees chose routes with shorter distance, less fire danger, and better pavement conditions. These results were significant and were similar between the utility- and regret-based models. For shelter choice, only safety was a significant attribute, while reentry timing was influenced only by permission to return and the need to check on people. Mode choice had no significant attributes.

Recommendation: Agencies should encourage evacuees to leave before they visually see the fire. While the precise time to issue mandatory evacuation orders is highly dependent on fire speed, wind, fuel loads, and geography, agencies should err on the side of caution to ensure that the slowest evacuees are able to leave. Alternatively, agencies could consider advanced trigger models that identify when officials should issue orders based on the fire and targeted evacuation clearance times. To accommodate these changes in departure time, agencies should also ensure transportation resources (e.g., public transit) and operations (e.g., shoulder use, parking restrictions, contraflow [i.e., reversing in-bound lanes], signal priority) are in place for early evacuees.

Recommendation: Agencies should increase evacuation information at the neighborhood level to leverage neighbor networks. Accurate evacuation information, particularly on planned departure times for a time-phased evacuation, should be distributed at a local level through different mechanisms (e.g., CBOs, CERTs, neighborhood associations). If a jurisdiction does not have established local disaster response mechanisms or local networks, agencies should consider integrating CBOs into emergency management roundtables, developing a CERT training program, and/or training neighborhood associations for disaster response.

Recommendation: Agencies should provide clear routing information, including routes not overtaken by fire, to reduce route uncertainty. This may require coordination with other jurisdictions and routing applications (e.g., Waze, Google Maps) to dynamically route around blocked roads (e.g., due to debris). Moreover, agencies need to leverage low-tech forms of communication if power is lost, mobile phones do not have coverage, or individuals do not have mobiles phones or data plans. This might include developing a radio system through which fire personnel can communicate with residents directly, without the need for power. Pre-planning of these communication mechanisms will be necessary and may require substantial coordination with utilities (e.g., power, telecommunications).

Recommendation: Agencies should prepare transportation operations at a highly localized level (as opposed to a multi-jurisdictional level) to reduce congestion. For example, agencies could implement signal priority, parking restrictions, and/or contraflow at critical intersections or along heavily used roads close to the wildfire impact area. Regional agencies (e.g., metropolitan planning organizations, public transit agencies), utilities, and other multi-jurisdictional agencies should also be prepared to help local agencies at the neighborhood level. If the wildfire impact area falls outside of regional jurisdictions, assistance would fall to agencies at the state level (e.g., a state department of transportation).

10.4.2) Comparison of Regret Minimization and Utility Maximization

<u>Conclusion: Random regret minimization (RRM) models failed to outperform traditional random utility maximization (RUM) models across wildfire choices, but additional studies with improved survey methodology and more data are likely needed for more conclusive results.</u>

To test the performance and behavioral implications of RUM and RRM models in evacuations, a revealed preference (RP) methodology was constructed for a survey of individuals impacted by the 2017 December Southern California Wildfires (n=226). The survey required respondents to provide their actual choices, two considered choices, and the attribute levels for all three choices. Using these data, RRM models were found to perform equally well or slightly worse than RUM models. Some weak attribute-level regret was found for departure timing (visual fire level), route (fire danger), and reentry timing (permission to return and pressure to return to job/work). A weak class of regret minimizing evacuees was found for both route and transportation mode. These results taken together suggest that RRM models likely do not outperform RUM models in a disaster context, failing to provide any additional behavioral nuances. Several limitations in the RP methodology may have produced these results including: a single data point per person; considered choice opt-out; attribute-level opt-out; and low attribute-level variation. This last limitation is especially problematic because the resulting regret function is close to linear for small sections (i.e., when attribute-level variation is low), which makes regret indistinguishable from linear-additive utility.

> Recommendation: The RP methodology should be improved by reducing the number of attributes shown to respondents and removing some considered choice sections that did not exhibit any regret minimizing behavior (e.g., shelter type). These improvements taken together would reduce considered choice opt-out and attribute-level opt-out. The methodology should also increase the number of beta testers to ensure that respondents understand the attributes and purpose of the considered choice section.

> Recommendation: A stated preference (SP) experiment should be administered to both previous evacuees and a general population. The SP experiment would make the construction of choice-sets easier, eliminate considered choice and attribute-level opt-out, increase attribute level variation, and collect multiple samples per individual. While an SP survey would reduce the level of realism, the survey could still be administered to people who recently experienced a disaster. This could be compared to results from an RP survey of evacuees and an SP survey of the general population to determine generalizability of results. An SP survey would also uncover regret minimizing behavior if it is present in choice making, since the randomized experiment would produce enough attribute-level variation. The evacuation field should continue experimenting and exploring alternative decision rules (including those beyond regret), which could better explain evacuation choice making.

10.5) Future Research Directions and Remaining Gaps

This dissertation makes important theoretical, methodological, and empirical contributions related to the sharing economy, (joint) choice modeling, and regret minimization, all in the context of evacuations. Despite this analysis, significant gaps remain in the literature that require more study. The next several sections contain remaining gaps in evacuation research, limitations of this dissertation, and future ideas and research directions that deserve further academic exploration.

10.5.1) Gaps in Empirical Data

While this dissertation made strides in collecting rich and beneficial data using three surveys, four focus groups, and 24 expert interviews, the evacuation field requires a more concerted effort to determine data needs, collect data for more disasters, and ensure that evacuation outcomes improve.

10.5.1.1) Survey Data

The analysis in this dissertation relies heavily on empirical data, mostly collected after disasters between 2017 and 2019 through online surveys. Despite this intensive data collection, however, more work is needed to test the generalizability of evacuation theories, models, strategies, and recommendations. A critical step to building generalizability is the collection of post-disaster survey data following all major disasters and human-made hazards that require evacuations. While this effort would require considerable funding and time, these data would allow for comparisons across geographies, cultures, and hazard types. Further, collection of data in the same location for multiple hazards (for example, post-hurricane surveys in Florida) can begin establishing longer-term trends through a panel survey. Little has been attempted in this area beyond Murray-Tuite et al. (2012), which studied changes in evacuation behavior between Hurricane Ivan (2004) and Hurricane Katrina (2005). While it is hard to retain individuals for a panel between surveys, this method (along with more systematic data collection) would uncover behavioral and perception changes, better inform traffic simulations, and determine what strategies are most effective.

In addition, more work is needed to determine if different survey methods (e.g., online vs. phone vs. mail-in) lead to different results. For example, mail-in surveys may severely undersample displaced individuals (who are also likely to be more vulnerable). Online surveys may address this displacement problem, but the method relies heavily on the types of platforms and the agencies used to distribute the survey. Overall, the evacuation field needs more rigorous data collection methodologies, particularly given the inability to conduct randomized controlled trials (RCTs) or even quasi-experiments (e.g., assigning evacuation routes during a disaster). More rigorous methodological approaches would help to generalize results and enable easier comparisons to assess evacuation behavior and best practices for the field (Bian et al., 2019). This need is particularly important, as data collection for evacuations must occur within a limited time window. Unlike other research areas that allow for routine sampling (for example, general travel behavior), the evacuation field is limited to the time frame surrounding a disaster.

10.5.1.2) Qualitative Data

The collection of qualitative data offers unique perspectives for the evacuation field. While a significant amount of work can be accomplished without employing focus groups or interviews, additional research is needed with respect to vulnerable populations. Given the limitations of surveying vulnerable populations, focus groups and in-depth interviews offer the opportunity for traditionally marginalized people to be heard. For example, Elder et al. (2007) conducted focus groups with African Americans in Columbia, South Carolina who were evacuated from Hurricane Katrina. For wildfires, Asfaw et al. (2019) used both interviews and focus groups to better understand evacuation preparedness and challenges for the Sandy Lake First Nation in Northern Ontario, Canada. These studies indicate that agencies should conduct community needs assessments at the local level to determine what more vulnerable populations need before, during, and after a disaster. Importantly, this process could improve equitable outcomes, with vulnerable populations playing an active role in planning.

Focus groups and in-depth interviews also reveal subtle nuances that cannot be determined via a survey. For example, the focus groups of vulnerable populations from the California wildfires uncovered that low trust of drivers (e.g., TNCs) and concerns for driver safety were both important limitations to a sharing economy strategy (see Chapter 5). Questions related to these concerns were not asked in any of the disaster surveys. Moreover, the focus groups allowed community members to offer their own recommendations for the sharing economy, often without being prompted. Researchers should also consider conducting more interviews with survivors directly following a disaster, including in shelters and disaster areas (Eisenman et al., 2007; Collins et al., 2018), to reduce the time between choice making and data collection.

10.5.1.3) Big Data

The rise of GPS-enabled mobile phones offers a unique and valuable opportunity for the evacuation field. By collecting mobile phone locations, researchers can now leverage "big data" to determine mobility patterns and some key evacuation choices. Data are also becoming less expensive and easier to collect. While research using large datasets is still in its infancy for the evacuation field (Yabe and Ukkusuri, 2020), initial opportunities exist in verifying traffic simulations of evacuations. Since traffic simulations often require a series of complex assumptions, big data can help determine model accuracy. In addition, big data can sometimes be more representative of the population when compared to surveys, focus groups, and interviews. However, social equity issues exist for big data, as populations without mobile phones will not be tracked or included in the dataset. Moreover, big data through mobile phones rarely collects demographic information, which then must be inferred by the researchers or simply ignored. Also, while people can be identified through GPS tracking, this process poses severe privacy concerns. Finally, big data offer *what* people did but does not tell researchers *why* they did it. This limitation may require a hybrid approach that connects mobile phone data and survey results.

10.5.2) Choice Modeling Challenges

Advanced discrete choice models developed in this dissertation (i.e., portfolio choice model, multi-choice latent class choice model, random regret minimization model) are an important step in the evacuation field toward considering alternative ways to explain behavior. However, each of these models contains limitations, which must also be addressed. The portfolio choice model (PCM), while able to capture decision-dimensional dependency (if present), is limited by the sample size of the data in terms of the number of portfolios and how the categories are split. In this dissertation, evacuation choices could be split into only two or three discrete categories, as further granularity in categories would produce a false sense of precision given the likelihood of measurement error. Moreover, categories with small sample sizes (for example, public shelters) had to be combined with other categories (in this case, hotels/motels), which diminished behavioral understanding. The PCM performs poorly (i.e., cannot find significant interactions) with low chosen alternatives unless combined with other alternatives (e.g., combining public shelters and hotels/motels compared to private shelters). Chapters 7 and 8 provide additional commentary on PCM limitations.

The multi-choice latent class choice model (LCCM) presented in Chapter 6 can capture unobserved class heterogeneity in a population across multiple scenarios or choices. While multi-choice LCCMs identify unique classes of people and their membership, the model is highly sensitive to the inclusion of additional parameters. This sensitivity is especially true with low sample sizes. Consequently, the multi-choice LCCM loses some behavioral richness and nuance, as some important class-specific or class-membership variables become insignificant in the model. These variables may exhibit significance for a lower number of classes, but this reduction would likely miss classes of behaviorally distinct people. In these situations, the modeler is challenged to carefully balance the number of classes, class-specific variables, and class-membership variables to produce a behaviorally consistent and significant model.

Random regret minimization (RRM) models employ an alternative decision rule based in regret theory to better understand and explain choice making. RRM models allow for semi-compensatory behavior (i.e., the improvement of one attribute may not offset the poor performance of another) and permit losses to be felt more than gains. Despite these behavioral nuances, the RRM models presented in Chapter 9 performed no better than traditional random utility maximization (RUM) models. Only weak regret-minimizing behavior was found in this revealed preference setting. Two important challenges arose from this research. First, RRM requires attributes of alternatives and at least three alternatives for estimation. In the evacuation field, attributes of alternatives are rarely considered in choice models, as researchers opt for demographic variables, risk perceptions, and hazard characteristics that are not alternative dependent. Consequently, the development of a choice experiment in which RRM could be estimated was difficult, particularly for a revealed preference survey. Second, RRM requires sufficient numerical differences in attributes to distinguish regret-minimizing behavior from utility-maximizing behavior. This was a primary issue with the revealed preference survey design in Chapter 9, which did not clearly determine if people were regret-minimizing in an evacuation.

Due to these challenges in choice modeling, several clear research directions exist. First, these advanced choice models (i.e., PCM, multi-choice LCCM, RRM) should be developed across hazards, geographies, and cultures to test for generalizability. Second, PCMs should be used to test for decision dependency, and results should be used to develop other joint models (i.e., nested logit, sequential logit) between highly significant decisions. Alternatively, PCMs could be developed to affirm joint models, such as those developed in Gehlot et al. (2018) and Bian et al. (2019). Third, multi-choice LCCMs should be developed as a consistent comparison against PCMs and extended across time (i.e., dynamically) to capture changes in choices throughout the evacuation process. Finally, RRM models must be further studied to determine if regret-based decision rules are applicable for evacuations. One clear extension of the work in Chapter 9 would be developing a choice experiment in a stated preference survey that has substantial variation in attributes.

10.5.3) Innovative Mobility Opportunities and Limitations

While this dissertation explored the sharing economy related to TNCs/ridehailing/ridesourcing and homesharing, other mobility innovations continue to sweep through the transportation sector (e.g., automated and connected vehicles, electric vehicles, other app-based mobility, micromobility, urban air mobility). These innovations could significantly affect travel behavior, land-use patterns, vehicle ownership, and even disaster response. One of the earliest adopted innovations will likely be battery electric vehicles (BEVs). Advances in battery technology and supply-side policymaking in the form of the California Advanced Clean Cars Program have steadily increased the number of BEVs on California roads. California is also aiming to achieve five million zero emission vehicles by 2030 (California Executive Order B-48-18) and decrease greenhouse gas (GHG) emissions from the transportation sector (pursuant of California AB 32, 2006). With other states following suit and the proliferation of cheaper and long-range electric vehicle options, BEVs could become a dominant fuel type, leading to natural disaster policy implications (Adderly et al., 2018) with benefits and severe limitations in evacuations and disasters for households, governments, and public transit agencies (Table 1).

Similarly, automated vehicles and connected vehicles (AVs and CVs) are altering the future of transportation and may achieve adoption in the coming decades. Government and academia are growing in their understanding of the potential benefits and limitations of AVs/CVs and the policies that must be crafted to prepare society for either shared or personal AVs (Fagnant and Kockelman, 2015). Some work has been conducted on how AVs could be routed in an evacuation (Ekram and Rahman, 2018; Chang and Edara, 2018), but research has yet to consider the policy implications, benefits, and limitations of AVs in disaster situations (Table 1). Considerably more research must be conducted to leverage the benefits of AVs/CVs, while minimizing the negative impacts.

Drones and urban air mobility (UAM) may offer an effective tool in improving compliance, congestion, and social equity in evacuations. Commercially available drones, which can be equipped with cameras, sensors, and other technology, are relatively inexpensive (particularly compared to helicopters) and can travel distances upward of ten miles with 30 minutes of flight time. Recent research has focused on the benefits and limitations of drones for disaster response and humanitarian relief (Apvrille et al., 2014; Estrada and Ndoma, 2019), but work specifically focused on evacuations is needed. UAM using vertical take-off and landing (VTOL) vehicles is a developing mode of passenger transportation for short to medium distances across urban environments. While revenue service may not be operational for some time, UAM vehicles could transport trapped evacuees or deliver relief supplies (Table 1) similar to the use of helicopters in the 2017 Atlas Fire (Lewis, 2018).

Table 1: Preliminary Benefits and Limitations of Example Innovative Mobility

Preliminary Benefits of Innovative Mobility	Preliminary Limitations of Innovative Mobility
Battery Electric Vehicles (BEVs)	
Act as a battery that could deliver electricity back to the grid, infrastructure (i.e., medical equipment), or mobile phones	Charging may lead to peak demand of electricity prior to evacuations
Reduce the logistical needs of transporting gasoline	Charging becomes challenging if power is unavailable
Reduce GHG emissions from evacuations	Limited vehicle range or low battery charge prohibits most long-distance trips

Increase short- and medium-distance evacuations, which decreases congestion, reentry times, resource use	Operational challenges in power outage for public transit agencies with extensive network of trolley and/or electric buses
Automated and Connected Vehicles (AVs and CVs)	
Conduct point-to-point rides to increase accessibility	Challenges with navigating debris or downed power lines
Provide rides to carless individuals	Challenges with non-trivial navigation (i.e., flooded or burning roads)
Successfully navigate local roads to avoid and reduce congestion	Challenges with routing around cracked or damaged roadways
Increase situational awareness through video or other data	All limitations related to EVs, if the AV is electric
Drones and Urban Air Mobility (UAM)	
Transport relief supplies to impacted areas	Increased risk of crashes due to adverse weather conditions
Ferry evacuees above hazardous zones	Low capacity of vehicles compared to surface vehicles (UAM only)
Circumvent surface congestion and traffic	Require substantial space to take off and land, which may not be available if infrastructure is compromised (UAM only)
Gather real-time data on traffic conditions and damaged areas and communicate with residents via sirens and loudspeakers	Similar charging limitations to EVs if power is unavailable (as drones and VTOL vehicles may also be electric)

Micromobility (including bikesharing and scooter sharing) and microtransit could also provide flexible modes for evacuations and recovery, particularly in dense urban environments and for those without access to vehicles. For example, bicycles were used following the Mexico City Earthquake in 2017 to transport people, goods, and relief supplies (Jong, 2017). Disaster Relief Trials (DRTs) are a series of disaster drills simulating supply runs using cargo bikes that have gained support from cities and FEMA (Adolph, 2013; Kirby, 2014; Murphy, 2017). Research is needed to determine the effectiveness of micromobility, particularly given increased risks for cyclists posed by evacuating vehicles and the hazard. Moreover, some people will be physically unable to cycle. On the other hand, microtransit through small vans or buses could be a more flexible and robust strategy, especially for assisting carless populations. Finally, traditional public transit offers an opportunity for enhancing transportation access in disasters and should not be discounted.

10.5.4) Resilience and Sustainability Disconnect in Evacuations

Limitations of innovative mobility modes and services, particularly electric-based forms, also point to a broader issue in disasters and evacuations related to a resilience and sustainability disconnect. Generally, resilience can be defined as "the capacity of social, economic and environmental systems to cope with a hazardous event or trend or disturbance, responding or reorganizing in ways that maintain their essential function, identity and structure, while also maintaining the capacity for adaptation, learning and transformation" (IPCC, 2014). Additional review of resilience definitions can be found in Trapenberg Frick and Forscher (2018). Sustainability is defined as "a dynamic process that guarantees the persistence of natural and human systems in an equitable manner" (IPCC, 2014) and is commonly considered in terms of environment, economy, and equity (Purvis et al., 2019). While resilience and sustainability have some similarities (e.g., long-term continuation) and co-benefits (e.g., increasing social equity, improving health and well-being, creating green infrastructure), the implications of these concepts in disasters can produce a severe disconnect. One example from the previous section is that BEVs (personal vehicles or buses) require electricity to power them. In the event of a major hazard, power may not be available to charge vehicles or electricity demand may overload the system. This disconnect between resilience and sustainability requires careful and thoughtful planning that achieves both goals. For example, hydrogen fuel cell vehicles, which operate on hydrogen fuel, could be a viable option that meets GHG emission reduction goals and remains relatively operational in a disaster (as fuel can be transported more easily or created onsite). However, given that the hydrogen fueling network is currently limited and EV infrastructure is being prioritized, this opportunity will be infeasible for some time. Other examples of linked sustainability and resilience goals that will require new strategies to produce positive evacuation outcomes (related to compliance, congestion, and social equity) include:

- Reducing vehicle miles traveled and auto dependency, while ensuring all people can evacuate quickly and safely;
- Reducing road capacity for private vehicles in exchange for more space for more sustainable transportation modes (i.e., bike lanes, public transit lanes), while increasing vehicle flow in an evacuation;
- Increasing density through land use changes, while reducing development in high-risk areas prone to disasters; and
- Building public transit infrastructure to increase ridership, while ensuring that a system will sustain minimal damage and can function in a disaster.

10.5.5) Public Safety Power Shutoffs – A New Hazard

The focus of this dissertation was on evacuations from natural hazards, specifically hurricanes and wildfires. However, little is known about how people behave in public safety power shutoff (PSPS) events and how they impact evacuations. PSPS events are a relatively new procedure undertaken by utilities to cut power in certain geographical areas determined to be at high risk for wildfires. While utilities use different risk criteria (e.g., high wind speed, drought conditions, high temperatures, low humidity, close proximity to high population areas, danger to electrical equipment) and make varying decisions on which type of lines to cut (e.g., transmission vs. distribution), the overarching goal of PSPS events is to reduce the likelihood of wildfires. The PSPS policy was first implemented in the U.S. by San Diego Gas & Electric (SDG&E) following the 2007 Southern California Wildfires, after officials found that downed power lines owned by SDG&E had sparked the Witch and Rice Canyon Fires (Nikolewski, 2017). One of the largest PSPS events in California (and the U.S.) occurred in early October 2019 when Pacific Gas & Electric (PG&E) shut off power to approximately two million people (Luna et al., 2019). A concerted research effort is needed to better understand choice making and travel behavior before, during, and after PSPS events. Moreover, research is needed to strengthen emergency response for key needs that rely on electricity (e.g., communication, transportation, etc.)

10.5.6) Future of the Evacuation Field

The evacuation field has grown considerably in the past twenty years, spurred by an escalating need to move large populations rapidly in the face of natural and human-made hazards. While evacuations have been largely regarded as a niche field, researchers and practitioners are beginning to think more holistically about transportation implications throughout the disaster cycle/phases (i.e., preparedness → response → recovery → mitigation). One reflection of this broadening view is the increase in research on the logistics of relief supplies, the reentry of individuals after disasters, and the development of transportation systems that are more resilient to acute shocks and chronic disruptions. Resilience, in particular, speaks to the connection of transportation with a multitude of other areas including land use, housing, social equity, environment, health, and safety. These complex and interdependent challenges require multidisciplinary thinking and collaboration. Multiple opportunities in transportation, ranging from public transit to innovative mobility, can be leveraged in disasters, but longer-term planning is an essential prerequisite to their success. Most importantly, as transportation, climate, and land use continue to change, evidence-based research will assume an even stronger role in informing more effective, safe, and socially equitable evacuations.

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