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## Understanding California Wildfire Evacuee Behavior and Joint Choice Making

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## **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 latent class choice models (LCCMs) to evaluate the factors that influence the decision to evacuate or stay/defend. We find an evacuation keen class and an evacuation reluctant class that are influenced differently by mandatory evacuation orders. This nuance is further supported by different membership of people to the classes based on demographics and risk perceptions. 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. Altogether, this paper provides evidence of heterogeneity in response to mandatory evacuation orders for wildfires, distinct membership of populations to different classes of people for evacuating or staying/defending, and clear correlation among key wildfire evacuation choices that necessitates joint modeling to holistically understanding wildfire evacuation behavior.

Keywords: Evacuations, evacuee behavior, California wildfires, latent class choice model, portfolio choice model, joint choice modeling

## 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 in California (see Table 1). Meanwhile, at least 10,000 people were ordered to evacuate 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. Decision-making begins when individuals decide if they will evacuate or stay in a wildfire evacuation, which is complicated by defending behavior where individuals 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; Kuligowski et al., 2020). However, variables that influence wildfire evacuation behavior remain only minimally supported by empirical evidence (i.e., only one or two studies). Moreover, it remains unclear if there exist different classes of individuals that behave differently in wildfire evacuations, as put forth by McCaffrey et al. (2018). This study offers new evidence on leveraging latent class choice models (LCCMs) to better understand wildfire evacuation behavior.

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 (Wong et al., 2020a). While work has been conducted to assess joint choice-making in hurricanes (Bian, 2017; Gehlot et al., 2018; Wong et al., 2020b), no work to our knowledge has employed joint choice modeling methods for wildfire behavior. Consequently, it remains unclear if behavior should be modeled jointly, which may offer nuances that could assist evacuation planning. Moreover, work is still needed to establish further consensus on the influencers of wildfire evacuation behavior, similar to continued research on hurricane evacuation behavior that occurs following each major hurricane.

To address the key literature gaps, we developed several research questions to guide our study:

- 1) What influences individuals to evacuate or stay/defend their home/property in a wildfire ?  
Do classes of people exist that make different evacuation choices and are composed of different people?
- 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: 1) developing two LCCMs, which capture the decision to evacuate or

stay/defend via unobserved segments of the sample, and 2) developing 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 offer research limitations and future directions of inquiry.

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

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

## 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.

### 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 (Cutter and Barnes, 1982; Stallings, 1984), and the eruption of Mt. St. Helens (Greene et al., 1981; Perry and Greene, 1982). 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. Discrete choice models are built on the assumption that individuals choose the alternative with the highest utility, or satisfaction. Ben-Akiva and Lerman (1985) provide 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), mixed logit (allowing for random parameters and capturing heterogeneity), and LCCM (capturing classes and membership to these classes based on unobserved preferences). 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., 2012), a mixed logit model for route choice (Sadri et al., 2014b), and a LCCM for the decision to evacuate or stay (Wong et al., 2020b).

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 evacuate 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 that jointly estimated transportation mode and destination type through a nested logit model (Bian, 2017) and estimated departure timing and travel times (a proxy for destination) through a joint discrete-continuous departure model (Gehlot et al., 2018). Finally, Wong et al. (2020b) developed a 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 identified significant relationships and interactions between the modeled choices, indicating the need to continue exploring joint behavioral models, regardless of hazard type.

Despite this work in hurricane evacuation behavior, key characteristics of hurricanes (such as temporal, spatial, and hazard risks) are different for wildfires (see Table 2). These differences likely lead to different behaviors across the hazards, requiring distinct transportation responses.

For example, hurricanes, with their long lead time, allow for more temporal phasing, while more rapid wildfires require fast communication and quick deployment of capacity-improving measures. Moreover, work by Wong et al. (2018) found evacuation compliance (i.e., receiving a mandatory evacuation and deciding to evacuate) for Hurricane Irma (2017) to be around 69%, while Wong et al. (2020c) found the rate to be around 90% for California wildfires. Literature has yet to directly compare hurricane and wildfire evacuation behavior using similar methods and survey designs. Given this gap, the next section focuses exclusively on wildfire hazards and the associated behaviors during evacuations, which is the primary topic of this paper.

**Table 2: Overview of Different Spatial, Temporal, and Hazard Characteristics between Hurricanes and Wildfires**

<b>Characteristic</b>	<b>Hurricane</b>	<b>Wildfire</b>
<b>Spatial</b>	<ul style="list-style-type: none"> <li>• Larger in size, impacting large geographies</li> <li>• Affects low-lying areas and coastal areas</li> <li>• Can impact millions of people</li> <li>• Often requires interstate cooperation</li> <li>• Produces more long-distance evacuations</li> </ul>	<ul style="list-style-type: none"> <li>• Smaller in size, impacting more localized areas</li> <li>• Concentrated in forested and chaparral environments</li> <li>• Can impact hundreds of thousands of people</li> <li>• Rarely requires interstate cooperation</li> <li>• Produces more short-distance evacuations</li> </ul>
<b>Temporal</b>	<ul style="list-style-type: none"> <li>• Long lead time and long-term notice</li> <li>• Often slower progression</li> <li>• Permits slower evacuations with longer mobilization time (e.g., several days)</li> <li>• Enables phased evacuation planning</li> <li>• Allows for slower communication response</li> </ul>	<ul style="list-style-type: none"> <li>• Short to no lead time and short-term notice</li> <li>• Often rapid progression</li> <li>• Requires fast evacuations with minimal mobilization time (e.g., several hours)</li> <li>• Partially restricts phased evacuation planning</li> <li>• Requires rapid communication response</li> </ul>
<b>Hazard Risks</b>	<ul style="list-style-type: none"> <li>• Primarily storm surge, wind, flooding</li> <li>• Cascading impacts on utilities</li> <li>• More predictable</li> <li>• Severity also dependent on the speed of the storm, land use, and development</li> </ul>	<ul style="list-style-type: none"> <li>• Primarily fire, heat, wind, and smoke</li> <li>• Cascading impacts on utilities and post-disaster landslide/mudslide events</li> <li>• Less predictable</li> <li>• Severity also dependent on the speed of the fire, land use, development, and fuel levels</li> </ul>

## **2.2 Wildfire Evacuation Behavior Research**

In recent years, evacuations from wildfires have grown in both frequency and scope. With substantial development along the wildland urban interface (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 between 2017 to 2019 from major wildfires (Wong et al., 2020c). 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 (Fisher III et al., 1995; Benight et al., 2004). This has been more recently expanded to consider defending behavior (McCaffrey and Rhodes, 2008; McCaffrey and Winters, 2011). 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, 2008), and the behavioral factors that impact wildfire decision-making (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. Recent work has also begun to develop cross-cultural analysis, such as by Vaiciulyte et al. (2021), on individual delay (i.e., time spent conducting activities before evacuating) in wildfire evacuations for the South of France and Australia. The work found that people will undertake actions (e.g., seeking information, gathering belongings, protecting property, preparing pets) that can lead to significant delays in a rapidly evolving situation. This research has helped start bridging gaps between different geographical and cultural contexts for more direct analysis of wildfire evacuation behavior and requires expansion to transportation choices.

To further understand wildfire evacuation behavior, some studies have employed discrete choice analysis, mostly for the decision to evacuate or stay/defend. Table 3 (adapted from Wong et al., 2020c) 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; Wong et al., 2020a; Kuligowski et al., 2020). Toledo et al. (2018), Lovreglio et al. (2019), and Kuligowski et al. (2020) 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 LCCM, finding a distinct evacuate class and a distinct defend class based on wildfire risk perceptions and attitudes. McCaffrey et al. (2018) also determined that the evacuate class was largely composed of people who decided to “leave early” or “wait and see.” Table 4 presents the significant factors found in these four studies on the decision to evacuate or stay/defend.

Most recently, Lovreglio et al. (2020) proposed a hybrid choice model that constructed a single latent variable of risk using external factors (i.e., physical cues), internal factors (i.e., demographic

variables), and risk indicators (e.g., perception of injury/death). The study focused on calibrating the Wildfire Decision Model, where people in a wildfire situation move through different states – normal, investigation, vigilant, and protective. The results found strong evidence that risk perceptions affect behavioral state, which can then lead to protective actions such as evacuating. In addition, recent work by Walpole et al. (2020) used a logistic regression to assess influencers on waiting behavior in an online, stated preference setting. Interestingly, the research found that those with a high attachment to place were less likely to wait during a wildfire after given strong physical cues and defense benefit information (i.e., information to defend the home in a wildfire). In addition to these decisions to evacuate, stay/defend, or wait, Wong et al. (2020a) developed both utility- and regret-based models to assess other key evacuation choices (i.e., departure timing, route, shelter type, transportation mode, and reentry timing). The study found that people displayed mostly utility-maximizing behavior and generally did not make evacuation decisions by minimizing future anticipated regret. However, attributes of choice alternatives (for both decision rules) were sometimes significant, indicating the need to focus on evacuation circumstances in wildfire choice making and transportation strategies.

**Table 3: Discrete Choice for Wildfire Evacuation Behavior (Adapted from Wong et al., 2020a)**

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 (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
Wong et al. (2020a)	Southern California Wildfires (2017)	Ventura County, Santa Barbara County, and Los Angeles County, California	Multinomial Logit; Regret Minimization	Departure Timing; Route; Shelter Type; Transportation Mode; Reentry Timing
Kuligowski et al. (2020)	Chimney Top 2 Fire (2016)	Gatlinburg and Pigeon Forge, Tennessee	Binary Logit	Evacuate or Stay/Defend

Walpole et al. (2020)	Hypothetical	Fire-Prone States, United States	Binary Logit	Waiting Intention
Lovreglio et al. (2020)	Chimney Top 2 Fire (2016)	Gatlinburg and Pigeon Forge, Tennessee	Hybrid Choice (with Latent Variable)	Risk Perception and Wildfire Decision States

**Table 4: Key Factors for the Decision to Evacuate or Stay/Defend for Discrete Choice Models using Revealed Preference Data (Significant Variables at 95% Confidence Level)**

Variable	Evacuate	Stay/Defend	Notes
<b>Demographics</b>			
Age 12 or under	Toledo et al. (2018)		Compared to age 35-54
Age 18-24		Lovreglio et al. (2019)	Compared to age 75+
Age 19-34	Toledo et al. (2018)		Compared to age 35-54
Age 55 and over	Toledo et al. (2018)		Compared to age 35-54
Gender (Female)	Kuligowski et al. (2020)		Compared to male
Higher Income		Toledo et al. (2018)	Very high
Lower Income		Toledo et al. (2018)	Very low or low
Household Size	Toledo et al. (2018)		Size 6 or more
Youngest Household Member 12 or Under	Toledo et al. (2018)		Compared to households without children
<b>Efficacy, Attitudes, and Risk Perceptions</b>			
Evacuation Efficacy	McCaffrey et al. (2018); Lovreglio et al. (2019)		Belief of ability to execute leaving behavior
Staying/Defense Efficacy		McCaffrey et al. (2018); Lovreglio et al. (2019)	Belief of ability to execute staying/defense behavior
Family Risk Attitude		McCaffrey et al. (2018)	Likelihood that in the next five years, a wildfire would threaten family's health and safety
Financial Risk Attitude	McCaffrey et al. (2018)		Composed of six variables related to the likelihood of various betting and investment strategies
Fire Risk	Toledo et al. (2018)		Whether or not houses on the same street as their home or near it were damaged
General Risk Attitude		McCaffrey et al. (2018)	Generally, someone who is fully prepared to take risks or someone who tries to avoid taking risks
Property Risk	Lovreglio et al. (2019)		Scaled 1 to 6
Property Risk Perception	McCaffrey et al. (2018)		Likelihood that in the next five years, a wildfire would threaten home/property
<b>Preparedness</b>			
Preparedness Knowledge		McCaffrey et al. (2018)	Knowing how to: 1) manage the vegetation around the home to decrease risks from wildfires, and 2) make structural changes to the home to decrease risks from wildfires
Self-Preparedness		Lovreglio et al. (2019)	Self-reported, scaled 0 to 4

Took Home Preparation Action		Kuligowski et al. (2020)	For example, fuel removal
Unwritten Disaster Plan	McCaffrey et al. (2018)		Household has a plan, but it is not written
<b>Wildfire Context and Risk Cues</b>			
Mandatory Evacuation Order	McCaffrey et al. (2018)		Evacuation warning
Voluntary Evacuation Order	McCaffrey et al. (2018)		Evacuation warning
Receiving Warning to Leave or Defend	Lovreglio et al. (2019)		For either leaving or defending
Official Cues	McCaffrey et al. (2018)		Composed of three variables related to the extent to which official and governmental warnings affect evacuation decisions
Physical Cues		McCaffrey et al. (2018)	Composed of five variables related to the extent to which visual fire, embers, visibility, wind, and distance of fire affect evacuation decisions
Risk Perception at Evacuation Time	Kuligowski et al. (2020)		Composite variable related to likelihood of injury/death of people and/or pets/livestock

Note A: Only significant variables (p-value  $\leq 0.05$ ) from discrete choice models using revealed preference data are shown

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., 2006; 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., 2015), 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). More advanced simulation models, such as the WUI-NITY platform, can also assist communities in visualizing wildfire spread, assessing human behavior and traffic congestion, and identifying trigger buffers (Wahlqvist et al., 2021).

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; Paz 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. Special focus has also been placed on assessing the evacuation behavior of indigenous populations and First Nations, indicating the need for place-based and people-specific policies strategies that address community needs (see for example, McGee et al., 2019; Christianson et al., 2019; Asfaw et al., 2020). 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.

### **2.3 Key Gaps**

Despite significant progress in understanding hurricane evacuation behavior, considerable gaps remain for wildfires. First, revealed preference studies using discrete choice analysis for wildfire evacuation behavior have not provided *consistent* evidence on the factors that influence behavior. For example, research found that both higher and lower income individuals were less likely to evacuate. Some risk attitudes and circumstances (though not equivalently asked) also produced different behaviors. In one case, Kuligowski et al. (2020) found that higher risk perception, based on likelihood of death/injury to people and animals, increased evacuations. In another, McCaffrey et al. (2018) found that risk perceptions based on higher physical cues increased staying/defending home/property behaviors. Moreover, as seen in Table 3, only a few variables were agreed on by two or more studies, showing a lack of corroborating evidence.

Second, while McCaffrey et al. (2018) built a LCCM for wildfires, the study's conclusions require additional support from different RP wildfire datasets. While Wong et al. (2020b) built a LCCM for hurricanes and Urata and Pel (2018) constructed a LCCM for tsunamis, the LCCM models remain underused in evacuations. LCCMs are still a novel approach to understanding evacuee behavior, and it remains unclear if classes and their associated membership provide additional behavioral understanding.

Third, 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 is unclear if choices in wildfire evacuations are correlated. Wong et al. (2020a) only considered transportation choices in isolation and focused predominately on decision-making rules, as opposed to correlated choice structures. In this paper, we address these three gaps by: developing: 1) two LCCMs for the decision to evacuate or stay/defend, and 2) two PCMs 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 from March to April 2019.

### **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.

#### **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., 2020c). The Thomas Fire started in the early evening of December 4 near Thomas Aquinas College north of Santa Paula and 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, 2017), while the Skirball Fire started along Interstate 405 near Bel-Air in Los Angeles on December 6 (Los Angeles Fire Department, 2017). The Skirball Fire was started by an illegal cooking fire (Los Angeles 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., 2020c), 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 (e.g., business-to-peer or peer-

to-peer sharing of resources, such as transportation or sheltering) 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 10 \$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. We also conducted another survey with individuals impacted by the 2017 Northern California Wildfires (n=79) using similar questions. The 2017 Northern California Wildfires affected Napa, Sonoma, and Solano counties, burned nearly 145,000 acres, and led officials to send evacuation orders to approximately 100,00 people (Wong et al., 2020c). Following the completion of that earlier survey, we modified and refined questions and responses to better capture evacuation choices for this research. We note that this process does not achieve similar internal validity as some of the best practice techniques and procedures currently available; we describe and acknowledge this in more detail in the limitations section. However, the earlier survey offered key insights into improving the design of the two surveys for this research. Table 5 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 5: California Wildfire Surveys**

	2017 Southern California Wildfires	2018 Carr Wildfire
<b>Survey Timeline</b>	March to July 2018	March to April 2019
<b>Targeted Counties</b>	Ventura, Santa Barbara, Los Angeles	Shasta, Trinity
<b>Targeted Fires</b>	Thomas, Creek, Skirball Fires	Carr Fire

<b>Incentive</b>	Drawing of five \$200 gift cards	Drawing of ten \$250 gift cards
<b>Responses</b>	552	647
<b>Finished Responses</b>	303	338
<b>Finish Rate</b>	55%	52%
<b>Cleaned Sample</b>	226	284
<b>Distribution Method</b>	Online via transportation agencies, emergency management agencies, community-based organizations, non-governmental organizations, and local media	

### **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 as shown in Wong et al., 2020a).

For this research, we focus our attention on developing a LCCM for the decision to evacuate or stay/defend and a 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 present models with more inefficiency that include more variables, rather than models that can lead to higher bias due to the exclusion of impacting variables. Given that risk perceptions are often correlated, we checked the correlation matrix for post-processed risk variables (i.e., very high/extreme perceptions vs. all other perceptions). Risk variables in the LCCMs and within each dimension of the PCMs exhibit correlations below 0.5 (with the majority under 0.3).

For the decision to evacuate or stay/defend, we first tested several binary logit models and mixed logit specifications. We found that mixed logit specifications offered little improvement in behavioral understanding or fit when heterogeneity was added. While the binary logit models were behavioral clear and simple to use, we chose the LCCMs for this paper since they offered a unique nuance related to mandatory evacuation orders (similar to results in Wong et al., 2020b). Moreover, measures of fit (AIC/BIC) were comparable to the other models. Future work should continue to test these different model types and specifications using data from other wildfires.

For the LCCMs, we used methodology in El Zarwi et al. (2017) and Wong et al. (2020b). First, we developed a class-specific model to find the probability that an individual  $n$  makes a choice

$y_{ni}$  to evacuate or stay/defend (where  $i = 1$  is evacuate and  $i = 0$  is stay/defend), conditional on the decision-maker belonging to latent class  $s$ . Thus, the utility of evacuation can be derived in equation (1), split between the systematic utility ( $V$ ) and errors ( $\varepsilon$ ) as:

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

The systematic utility is composed 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. Errors are drawn independently from an Extreme Value Type 1 distribution with a variance of  $\pi^2/6$ . Thus, the errors are considered independent and identically distributed (i.i.d.) random variables. We next normalize the systematic utility of staying/defending to 0 and calculate the class-specific probability to evacuate:

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

We note that while LCCMs can be composed of infinite classes, we chose two classes since the results were significant and behavioral clear. We tested a three-class model, and we found that two classes were nearly identical in how they responded to mandatory evacuation orders. Due to this similarity, we dropped one class and estimated a two-class model. We next built a membership model to determine which class an individual belonged to, based on demographics and risk perceptions. The probability that an individual belongs to the first class is  $P(q_{n1}|Z_n)$ , where  $\gamma'Z_n$  is the product of the coefficients and characteristics of the decision maker (composed in our case with demographics and risk perceptions). We assume the same error distribution as the class-specific model. The probability of class membership is:

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

We estimate the marginal probability of evacuating (combining equations 2 and 3) using a LCCM package developed by Yu (2020):

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

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. We recognize that decision-making in disasters likely follows some structure, especially to eliminate alternatives (or portfolios). Our goal in this paper is not to test large number of possible structures, which would be a time-consuming process. Rather, our goal is to identify possible correlations and interactions that can be considered in further depth with other discrete choice models. To test these structures, further exploration of dependencies between choice dimensions should be explored via nested logit and sequential logit models. For example, if we identify that destination is highly correlated with departure time, specific joint models can be tested for this situation (as seen in Bian, 2017). Ultimately, 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 Wong et al. (2020b).

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 6 below.

**Table 6: Consolidation of Choices for the PCM**

<i>Choices Considered</i>	<i>% of Evacuees (Southern California Wildfire)</i>	<i>% of Evacuees (Carr Wildfire)</i>	<i>Shorthand</i>
<b>Sample Size (Evacuees Only)</b>	<b>175</b>	<b>254</b>	
<b>Departure Day</b>			
Immediate Evacuees (Departed during the peak of wildfire threat)	61.1% (Dec. 4 & 5, 2017)	78.3% (July 26, 2018)	Immediate
Non-Immediate Evacuees (Departed outside the peak time of wildfire threat)	38.9%	21.7%	Non-Immediate
<b>Departure Timing by Hour</b>			
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
<b>Destination Choice</b>			
Evacuated inside same county as residence	66.3%	66.1%	Within County
Evacuated to a different county	33.7%	33.9%	Out of County
<b>Mode Choice</b>			
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
<b>Shelter Type</b>			
Private Shelter (Friends/Family/Other)	73.7%	84.2%	Private
Public Shelter (Public Shelter/Hotel/Motel)	26.3%	15.8%	Public
<b>Primary Route by Road Type</b>			
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**

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. PCMs are specified similarly to RUM models, which is covered extensively in Ben-Akiva and Lerman (1985). We express the utility for individual  $n$  for alternative (i.e., portfolio)  $i$  as:

$$U_{ni} = V_{ni} + \varepsilon_{ni} \quad (6)$$

where  $V_{ni}$  is the systematic utility of the portfolio and  $\varepsilon_{ni}$  are random disturbances. Again, we assume that the disturbances are i.i.d. Extreme Value Type 1 errors across all individuals and alternatives with a mean of zero and variance of  $\pi^2/6$ . One key feature of PCM is that the choice dimensions (designated as identical lists  $d$  and  $d'$ ) are now attributes that comprise the systematic utility as primary variables (see Dellaert et al., 1999 for details). The utility of each alternative 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). These first order interaction effects can also be added to the systematic utility:

$$V_{ni} = \underbrace{\sum_d V_{nd}}_{\text{Primary}} + \underbrace{\sum_{d \neq d'} V_{nd \cdot nd'}}_{\text{Interactions}} + \underbrace{\sum_d \gamma' Z_{nd}}_{\text{Demographics}} \quad (7)$$

where  $V_i$  is the systematic utility of the primary attributes (i.e., the choice-dimensions) and  $V_{d \cdot d'}$  is the systematic utility of their interactions. Demographic and risk perception variables (and their associated coefficient) may also be added for each primary dimension. We can now calculate the probability associated to a specific portfolio as:

$$P_n(i) = P(V_{ni} + \varepsilon_{ni} \geq V_{nj} + \varepsilon_{nj}, \forall i \neq j) = \frac{\exp(V_{ni})}{\sum_{j=1 \dots J} \exp(V_{nj})}$$

Since we have closed form logit probabilities, 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. This is especially problematic with a lower sample size. 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 6) 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 (or for a certain ratio of participants to choose portfolios). As noted in Wong et al. (2020b), 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. We do recognize that smaller sample sizes inhibit generalization and precision but do not invalidate the model. Finally, we separate both the LCCM 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.

#### **4. EVACUATE OR STAY MODEL RESULTS**

We next present results from two LCCMs for the decision to evacuate or stay/defend in Table 7. We focus on significant variables in these results, but we provide some non-significant variables in the model that will require additional research.

We found that individuals impacted by the 2017 Southern California Wildfires and the 2018 Carr Wildfire comprised two classes of people. The evacuation reluctant class (class 1) had a negative value for the constant, indicating that individuals in this class were less likely to evacuate (hence our short-hand label of reluctant). The constant was significant to 99.9% confidence for the 2017 Southern California Wildfires but only 90% confidence for the 2018 Carr Wildfire. For both fires, individuals in this class were more likely to evacuate if they received a mandatory evacuation, corroborating years of evacuation research (Lindell and Perry, 2003; Lindell et al., 2019). This indicates that mandatory evacuation orders, in some cases, may be sufficient to overcoming a preference for staying/defending.

The evacuation keen class had a positive value for the constant, indicating that individuals in this class prefer to evacuate (hence our short-hand label of keen). Mandatory evacuation orders also increased evacuation likelihood, but the influence of this variable was less pronounced than for the evacuation reluctant class. The implication of the behavioral nuance found in the LCCMs is that there exists heterogeneity in preference to evacuate or stay/defend and in how people respond to evacuation orders. The results indicate that mandatory evacuation orders must be targeted, especially to the evacuation reluctant class, as they would be significantly less likely to evacuate without an order. Meanwhile, the evacuation keen class will be more likely to evacuate, even without any orders. Overall, the results verify long-standing and significant evidence from discrete choice models in the evacuation field that mandatory evacuation orders are effective for wildfires (e.g., McCaffrey et al., 2018; Lovreglio et al., 2019), hurricanes (e.g., Whitehead et al., 2000; Wilmot and Mei, 2004; Hasan et al., 2011; Hasan et al., 2012; Huang et al., 2012; Yin et al., 2016; Wong et al., 2018) and other hazards (e.g., Murray-Tuite and Wolshon, 2013; Lindell et al., 2019).

##### **4.1. 2017 Southern California Wildfire Membership Model**

To understand this potential opportunity to send targeted orders to evacuation reluctant individuals, we also developed a membership class model that includes demographic and risk perception variables. For the 2017 Southern California Wildfire, we found that those with a strong belief of utility loss and fast fire spread (i.e., high risk perceptions) were more likely to be in the evaluation keen class (thus more likely to evacuate). These results corroborate evidence in evacuation research (e.g., Lindell et al., 2019) and wildfire research (e.g., McCaffrey et al., 2018; Lovreglio et al., 2019; Kuligowski et al., 2020) of the important effects of risk perceptions on evacuation decisions. Moreover, the work parallels the existence of latent factors tied to risk perceptions that Lovreglio et al. (2020) also found.

We found that those living in the same residence for more than 10 years, households with children (i.e., families), and individuals with higher level degrees (Master's and above) were all more likely to be part of the evacuation keen class. Toledo et al. (2018) for wildfires and other work in hurricanes (e.g., Smith and McCarty, 2009; Solis et al., 2010; Hasan et al., 2011; Hasan et al.,

2012; Yin et al., 2016; Wong et al., 2018) found similar results for families being more likely to evacuate. Hasan et al. (2011) and Yin et al. (2016) also found that higher education correlated with a higher likelihood to evacuate for hurricanes, but Riad et al. (1999) found that long-time residents were more likely to stay, countering our results.

Previous evacuees and those with wildfire experience (i.e., one or more wildfires) were more likely to be part of the evacuation reluctant class, suggesting that they would be less likely to evacuate but could be heavily influenced by mandatory evacuation orders. Literature on hurricane evacuations is split on these variables, with Riad et al. (1999) noting that previous evacuees were more likely to evacuate but Wong et al. (2018) showing that they were less likely to evacuate. Research is also split on hazard experience as Solis et al. (2010) and Murray-Tuite et al. (2012) concluded that hazard experience increases evacuation likelihood, but Hasan et al. (2012) found that experience decreases likelihood. Our results indicate that neighborhoods that have evacuated in prior wildfires or experienced nearby wildfires (e.g., seeing flames, smelling smoke) were hesitant to leave but could be influenced to evacuate with a mandatory order.

#### **4.2. 2018 Carr Wildfire Membership Model**

For the 2018 Carr Wildfire, we found similar results that risk perceptions (i.e., strong belief of utility loss, structural damage) influenced likelihood to be part of the evacuation keen class (similar to past research, including in wildfires such as McCaffrey et al., 2018; Lovreglio et al., 2019; Kuligowski et al., 2020). Our research also corroborates work by Lovreglio et al. (2020) of the existence of latent factors tied to risk perceptions, which can impact choice making in evacuations. We note that a strong belief of being injured or killed was significant to 90% confidence, but these individuals were more likely to part of the evacuation reluctant class. Further work will be necessary across datasets to determine the significance and direction of this risk perception variable, as this runs counter to past research and our expectation.

Long-time residents, previous evacuees, and those with frequent experience to wildfires (i.e., three or more wildfires) were also more likely to be evacuation reluctant. The variable for long-time residents parallels results for hurricanes in Riad et al. (1999) but runs counter to the model for the 2017 Southern California Wildfires. The results for previous evacuee mirror conclusions by Wong et al. (2018) and the 2017 Southern California Wildfire LCCM model. The hazard experience variable is similar to results for hurricanes in Hasan et al. (2012) and the 2017 Southern California Wildfire LCCM mode but not hurricane model results in Solis et al. (2010) or Murray-Tuite et al. (2012). Those living in a high fire risk zone (as denoted by the California Department of Forestry and Fire Protection [Cal Fire]) were more likely to be part of the evacuation keen class, along with females and young adults. The result adds to the consensus from hurricane evacuations (Riad et al., 1999; Whitehead et al., 2000; Smith and McCarty, 2009) that females are more likely to evacuate. For the age variable, Toledo et al. (2018) found that young adults were more likely to evacuate but Lovreglio et al. (2019) found the opposite, which altogether indicates uncertainty of age in evacuation decision-making for wildfires.

Finally, we tested income variables (high vs. low, with middle as the base), finding that higher income households (e.g., \$100,000 or more per year) were more likely to be in the evacuation keen

class while lower income households (e.g., less than \$50,000 per year) were more likely to be evacuation reluctant. The low-income result is similar to evidence in Toledo et al. (2018) for wildfires and some (but not all) hurricane literature (Zhang et al., 2004; Murray-Tuite et al., 2012). Transportation and sheltering resource availability may be driving this income difference.

### 4.3) Implications for Mandatory Evacuation Orders

Based on the LCCM results, we found that there exist two classes of people that have different preferences for evacuating but respond similarly, albeit with different magnitudes to mandatory evacuation orders (similar to results in Wong et al., 2020b). The results suggest that members of the evacuation reluctant class could be convinced to evacuate if they receive a mandatory evacuation order, while those in the evacuation keen class will likely evacuate regardless of an order. Consequently, agencies may have difficulty evacuating neighborhoods that have previous evacuated or experienced wildfires. Results also found that for one wildfire (Carr Wildfire), agencies may need to target long-time residents and lower-income households with mandatory evacuation orders (i.e., such as with greater frequency or more delivery methods). These results are not surprising and align well with theoretical and empirical understandings of risk communication (Lindell and Perry, 2003). They also correspond to unique differences in how people respond and react to disasters warning and evacuation orders (see Perry et al., 1982 for early examples). We also note that the two wildfires produced different, albeit similar results within the class membership models. Geographic, cultural, and context-specific distinctions could be at play, indicating that local agencies will need to assess community reaction to mandatory evacuation orders before a disaster. One context-specific distinction was that the 2017 Southern California Wildfires affected a larger population in a shorter amount of time, particularly at the onset of the disaster (see Wong et al., 2020 for a detailed description of both events). While decision-makers had more time to react in the Carr Wildfire, outdated communication methods notably hampered the distribution of evacuation notifications. Differences in results could also be cultural – the area around the Carr Wildfire is more rural than Southern California. Further research may need to ask specific questions about culture or experiences with the evacuation operations to identify why differences exist in the results. Finally, we note that this research establishes that heterogeneity, in the influence of mandatory evacuation orders on the decision to evacuate or stay/defend, is also prevalent for wildfires.

**Table 7: Evacuate or Stay/Defend Modeling Results**

Variable	2017 Southern California Wildfires			2018 Carr Wildfire	
	Est. Coef.	p-value		Est. Coef.	p-value
<b>Class 1 - Evacuation Reluctant</b>					
Constant	-1.20	0.001 ***		-0.55	0.076 †
Mandatory Order	1.53	0.001 ***		2.23	0.000 ***
<b>Class 2 - Evacuation Keen</b>					
Constant	2.39	0.00 ***		2.72	0.000 ***
Mandatory Order	1.30	0.059 †		1.44	0.045 *

	<b>Est. Coef.</b>	<b>p-value</b>		<b>Est. Coef.</b>	<b>p-value</b>	
<b>Membership Class 2 (Evacuation Keen)</b>						
Constant Class 2	-0.02	0.494		0.70	0.121	
<b>Risk Perceptions</b>						
Strong Belief of Utility Loss	1.05	0.002 **		0.73	0.015 *	
Strong Belief of Structural Damage	-----	-----		0.98	0.009 **	
Strong Belief of Fast Fire Spread	1.22	0.001 **		-----	-----	
Strong Belief of Being Injured or Killed	-----	-----		-0.74	0.089 †	
<b>Household Characteristics</b>						
Impacted by the Thomas Fire	0.02	0.486		-----	-----	
Pets in Household	-0.41	0.142		-0.21	0.301	
More than 10 Years in Residence	0.83	0.014 *		-0.54	0.050 *	
Living in a High/Very High Fire Risk Zone <sup>1</sup>	0.22	0.283		0.67	0.021 *	
Higher Income (Household income of \$100,000 or more per year)	-0.39	0.154		1.21	0.001 ***	
Lower Income (Household income below \$50,000 per year)	-0.21	0.367		-0.86	0.012 *	
Children in the Household	1.25	0.003 **		-----	-----	
<b>Individual Characteristics</b>						
Higher Level Degree (Master's, Professional, Doctorate)	1.66	0.001 ***		-----	-----	
Homeowner	-0.39	0.183		-----	-----	
Female	0.51	0.095 †		0.57	0.039 *	
Previous Evacuee	-0.73	0.030 *		-0.59	0.055 †	
Young Adult (under 35)	-----	-----		0.95	0.025 *	
Older Adult (65 or more)	0.57	0.122		-----	-----	
Frequent Experience with Wildfire (3 or More Wildfires)	-----	-----		-0.98	0.003 **	
Experience with a Wildfire (1 or more)	-0.83	0.014 *		-----	-----	
<b>Number of Observations</b>	284			284		
<b>Number of Parameters</b>	19			17		
<b>Final Log-Likelihood</b>	-87.3			-66.7		
<b>AIC</b>	212.5			167.5		
<b>BIC</b>	281.9			229.5		
Significance: †90%, *95%, **99%, ***99.9%						

<sup>1</sup> Self-reported survey question for: High or Very High Fire Hazard Severity Zone (FHSZ) as defined by Cal Fire

## 5. PORTFOLIO CHOICE MODEL RESULTS

We next present results of two PCMs 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 insignificant, 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 some possibility for future research. As noted in Wong et al. (2020b), 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 and models 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.

### **5.1 2017 Southern California Wildfires - PCM Results**

In Table 8 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 included: a joint preference for within county and private shelter; a joint dislike for within county and highway; and a joint dislike for multiple vehicles and highway.

**Table 8: Southern California Wildfire PCM Results**

Variable	Primary + Interactions			Primary + Interactions + Demographics		
	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	
<b>Immediate</b>								
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	*
<b>Night</b>								
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	***
<b>Within County</b>								
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	**
<b>Private Shelter</b>								
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	
<b>2+ Vehicles</b>								
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	*
Lower Income (Household income below \$50,000 per year)	-----	-----	-----		-0.94	0.64	0.143	
Previously Experienced Wildfire	-----	-----	-----		0.91	0.66	0.163	
Own 2 or More Vehicles	-----	-----	-----		1.51	0.38	<0.001	***
<b>Highway</b>								
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: †90%, \*95%, \*\*99%, \*\*\*99.9%

For departure day, we found that older adults were less likely to evacuate during the height of the wildfires. 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. 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 up until the fire reached their property. 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.

We found that individuals who received a voluntary evacuation order were less likely to evacuate at night. However, those with an extreme likelihood belief of structural damage were more likely to evacuate 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 (Wong et al., 2020c).

For 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 of traffic, higher-level degree (e.g., Master’s, professional, doctorate), 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 survey and PCMs.

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. Individuals with extreme likelihood belief of injury/death were more likely to stay at a private shelter. Other variables that were insignificant and should be tested in future work included: risk perception of structural damage, females, individuals with disabilities, and older adults.

Individuals who received a mandatory evacuation order were more likely to evacuate with two or more 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 availability and wanting to

protect their vehicles. 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, but individuals who received a voluntary evacuation order were more likely to use a highway. The reasoning for these results is not readily clear.

### 5.2 2018 Carr Wildfire – PCM Results

In Table 9 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.

**Table 9: Carr Fire PCM Results**

Variable	Primary + Interactions			Primary + Interactions + Demographics			
	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	†
<b>Immediate Departure</b>							
Extreme Likelihood Belief of Injury or Death	-----	-----	-----	-1.41	0.50	0.005	**
Homeowner	-----	-----	-----	0.68	0.42	0.107	

Lower Income (Household income below \$50,000 per year)	-----	-----	-----	-0.91	0.38	0.017	*
Living in Residence for More than 10 Years	-----	-----	-----	-0.66	0.36	0.067	†
<b>Nighttime</b>							
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	†
Lower Income (Household income below \$50,000 per year)	-----	-----	-----	1.38	0.47	0.003	**
<b>County</b>							
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	†
<b>Private</b>							
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	***
<b>2+ Vehicles</b>							
Children Present in Household	-----	-----	-----	1.34	0.33	<0.001	***
Lower Income (Household income below \$50,000 per year)	-----	-----	-----	-0.91	0.35	0.010	**
Extreme Likelihood Belief of Injury or Death	-----	-----	-----	1.02	0.30	0.001	***
Own 2 or More Vehicles	-----	-----	-----	0.80	0.31	0.008	**
<b>Highway</b>							
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: †90%, *95%, **99%, ***99.9%							

For immediate departure variables, we found that those with an extreme likelihood belief of injury or death were less likely to depart at the height of the wildfire. This result might be influenced by the construction of the choice dimension; 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 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. Individuals with a high-risk perception (e.g., likelihood of injury/death) and lower-income households (i.e., under \$50,000 per year) were more likely to evacuate at night.

For 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 these individuals probably have additional income and/or connections outside the area to travel further distances. Non-significant variables that require additional analysis include strong belief in work requirements and households with pets.

Those who believed they would have 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 runs opposite of results from the Southern California Wildfire PCM. Geographical and cultural context may be impacting directionality. Those worried about finding housing were more likely to shelter at a hotel or public shelter. Finally, those with a disability were less likely to shelter with friends/family.

For mode of transportation, 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, but homeowners were less likely to use highways. 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.

## **7. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS**

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. More representation of possible independent variables such as communication influences, social network impacts, or preparedness actions (as studied for example in Cohn et al., 2006; Stidham et al., 2011; McLennan et al., 2012; or Cote and McGee, 2014) is also important for future RP surveys. The development of systematic question banks could help ensure that these variables are included in further research.

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 that we did not ask about mobilization time or family gathering (i.e., reunification prior to evacuation), which has been shown to impact the decision to evacuate or stay/defend (e.g., Liu et al., 2012; Sadri et al., 2013; Liu et al., 2014; Toledo et al., 2018). Future surveys should ask questions related to these influencers. We also note that our future surveys should have more information about the characteristics of the hazard and risk perception variables that mirror other wildfire research (e.g., McCaffrey et al., 2018; Lovreglio et al., 2019; Kuligowski et al., 2020). Indeed, we found that individual and household characteristics sometimes had mixed signals depending on the hazard and the model, making it difficult to assess our results in the context of past research. Consequently, we recommend that future research using discrete choice modeling begin to assess attribute/characteristics of alternatives more systematically. Another key limitation is our usage of a LCCM to understand evacuee behavior. While other models account for sample heterogeneity (i.e., mixed logit), we found that these type of model did not provide additional behavioral insights. 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. Some portfolios may also not be available to evacuees. The issues of portfolio availability and heuristics to eliminate portfolios will require more research into the PCM modeling approach, including via qualitative methods, and should be address in separate methodological studies. We 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. The PCMs were subdivided for transportation mode into two or more vehicles versus all other responses. We recognize that this is an imperfect division, as the behavioral difference between households without cars and households with cars would likely be the clearest. However, our low sample size of carless households (a result of both

the online survey distribution and the location of the wildfires in areas with high car ownership) prevented us from splitting transportation mode in this way. Consequently, we highly recommend that future work better survey carless households. We also note that the full PCMs contain many demographic variables, including insignificant variables. We kept these additional 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. However, we also acknowledge that low sample sizes can inhibit our ability to identify parameters (including demographic variables), which may be leading to the low fit in our models.

Our research is also limited in the generalizability of its results to other wildfires, even those in California. This prevented us from reaching any strong recommendations for public agencies to build wildfire-specific evacuation plans. We recommend that more data be collected from wildfires (similar to significant data collection efforts following hurricanes) to make more robust recommendations that are empirically grounded and highly specified for wildfires. Cues can be taken from cross-cultural efforts, such as Vaiciulyte et al. (2021). We note that strategies for evacuations (mostly derived from hurricanes) do not (in their current form) address the unique risks of wildfires nor the impacts on different geographies, land use, and cultures. Significantly more research is needed to build wildfire-specific strategies, but this work aims to be a steppingstone for future ideas and recommendations.

Finally, we acknowledge several methodological limitations that can be addressed in future studies. First, a cross-data analysis was not conducted to identify the precise differences between the two datasets. This pre-modeling step can be taken in future work to determine if the datasets can be combined or should be separated. Second, our focus in this analysis is less on wildfire specific circumstances and attributes, which is extensively covered in Wong et al. (2020a). Future work should begin to add these attributes (along with risk perceptions and demographic variables) into a more holistic model, especially for the decision to evacuate or stay/defend homes/property. Third, our RP survey design methodology did not include consistency tests (e.g., Cronbach's alpha) or additional procedures such as principal component analysis (PCA). The same PCA procedure can help pre-process variables (such as risk perceptions) to overcome correlation structures and ensure validity in the RP survey. Our oversight in leveraging these key tools is a limitation of our research and should be considered in best practices for future work in the evacuation field.

## 8. CONCLUSIONS

In this study, we presented a comprehensive analysis of wildfire behavior using: 1) two latent class choice models (LCCMs) 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 that two classes of people exist – evacuation keen and evacuation reluctant – with different preferences for evacuation behavior. In both classes, mandatory evacuation orders increased likelihood to evacuate, but this effect was larger for the evacuation reluctant class. The

implication is that response to mandatory evacuation orders is heterogeneous. In terms of class membership, we found that those with risk perceptions (i.e., related to utility loss, structural damage, and fast fire spread) were more likely to be evacuation keen. Females, families, and those with a higher education, those living in a high fire risk zone, households with higher income (above \$100,000 per year), and young adults were more likely to be part of the evacuation keen class in at least one of the two wildfire models. For both wildfire models, previous evacuees were more likely to part of the evacuation reluctant class. Households with a lower income (below \$50,000 per year), those with wildfire experience, those with frequent wildfire experience (three or more wildfires), and those with a strong belief of possible injury or death were more likely to be part of the evacuation reluctant class in at least one of the two wildfire models. Long-term residents were more likely to be in the evacuation keen class for the 2017 Southern California Wildfires, but more likely to be in the evacuation reluctant class for the 2018 Carr Wildfire. In all, variables were similar but not identical between wildfire models. Demographic variables did not always provide a clear picture of influence or directionality, a similar result to research on hurricane decision-making (Lindell et al., 2019).

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 only somewhat similar 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 key step for wildfire evacuation behavior research to begin building more consensus on key choices and influencers of these choices.

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## 10. AUTHOR CONTRIBUTIONS

Stephen Wong: Conceptualization, Methodology, Formal Analysis, Investigation, Data Curation, Writing – Original draft preparation, Writing – Reviewing and Editing, Project Administration, Funding Acquisition

Jacquelyn Broader: Investigation, Writing – Original draft preparation, Writing – Reviewing and Editing

Joan Walker: Conceptualization, Investigation, Writing – Reviewing and Editing

Susan Shaheen: Conceptualization, Investigation, Writing – Reviewing and Editing, Supervision, Funding Acquisition

## 11. CONFLICT OF INTEREST STATEMENT

On behalf of all authors, the corresponding author states that there is no conflict of interest.

## 12. DATA STATEMENT

Data used for this study can be accessed through Zenodo at the following links.

Wong, S., Walker, J., & Shaheen, S. (2021). 2017 December California Wildfires Evacuation Survey Data. Embargoed until July 2021. <http://doi.org/10.5281/zenodo.4407730>

Wong, S., Walker, J., & Shaheen, S. (2021). 2018 Carr Wildfire Evacuation Survey Data. Embargoed until July 2021. <http://doi.org/10.5281/zenodo.4408243>

## 12. APPENDIX

**Table A1: Demographic Characteristics of Survey Respondents**

	2017 Southern California Wildfires	2018 Carr Wildfire
<b>Sample Size (All Respondents)</b>	<i>n</i> =226	<i>n</i> =284
<b>Individual Characteristics</b>		
<b>Gender</b>		
Male	26.1%	30.3%
Female	73.9%	69.7%

<b>Age</b>		
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%
<b>Race</b>		
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%
<b>Ethnicity</b>		
Hispanic	11.1%	5.3%
Not Hispanic	76.1%	87.3%
Prefer not to answer	12.8%	7.4%
<b>Education</b>		
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%
<b>Employment</b>		
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%
<b>Primary Mode of Transportation*</b>		
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%

<b>Decision-Making Role</b>		
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%
<b>Previous Evacuee*</b>		
Yes	35.3%	31.0%
No	64.7%	69.0%
<b>Previous Wildfire Experience**</b>		
Yes	93.4%	89.1%
No	6.6%	10.9%
<b>Cell Phone Type</b>		
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%
<b>Access to Internet at Home</b>		
Yes	98.7%	97.2%
No	1.3%	2.8%
<b>In-Vehicle or Smartphone Navigation***</b>		
Yes	79.6%	78.2%
No	20.4%	21.8%
<b>Household Characteristics</b>		
<b>Displacement after Wildfire</b>		
Same Residence	88.9%	87.0%
Displaced	10.6%	13.0%
No answer	0.4%	0.0%
<b>Length of Residence†</b>		
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%
<b>Residence Structure†</b>		
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%
<b>Homeownership†</b>		
Yes	67.3%	81.3%

No	29.6%	17.3%
Prefer not to answer	3.1%	1.4%
<b>Live in Cal Fire High Risk Area††</b>		
Yes	38.1%	37.7%
No	28.8%	35.2%
I don't know	33.2%	27.1%
<b>Household Characteristics</b>		
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%
<b>Household Income</b>		
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%
<b>County of Residence</b>		
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**

	<b>2017 Southern California Wildfires</b>	<b>2018 Carr Wildfire</b>
<b>Sample Size (All Respondents)</b>	<i>n</i> =226	<i>n</i> =284
<b>Evacuation Choice</b>		
Evacuated	77.4%	89.4%
Did Not Evacuate	22.6%	10.6%
<b>Sample Size (Evacuees Only)</b>	<i>n</i> =175	<i>n</i> =254
<b>Departure Timing by Hour</b>		

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%
<b>Shelter Type</b>		
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%
<b>Primary Route by Road Type</b>		
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%
<b>Usage of GPS for Routing</b>		
Yes, and followed route	18.3%	7.5%
Yes, but rarely followed route	4.6%	5.5%
No	77.1%	87.0%
<b>Multiple Destinations</b>		
Yes	41.7%	48.4%
No	58.3%	51.6%
<b>Returned Home</b>		
Yes	92.6%	96.9%
No	7.4%	3.1%
<b>Within County Evacuation</b>		
Yes	66.3%	66.1%
No	33.7%	33.9%
<b>Mode Choice*</b>		
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 ( <i>n</i> =226)		Evacuation Decision	
		Yes	No
<b>Received Mandatory Evacuation Order</b>	Yes	87.0%	<b>13.0%</b>
	No	<b>62.5%</b>	37.5%
	Total	77.4%	22.6%

  

2018 Carr Wildfire ( <i>n</i> =284)		Evacuation Decision	
		Yes	No
<b>Received Mandatory Evacuation Order</b>	Yes	96.8%	<b>3.2%</b>
	No	<b>75.0%</b>	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	
<b>Departure Day</b>			
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%
<b>Destination by County</b>			
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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