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

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ABSTRACT

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

1. Introduction

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

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

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intuitively resonates with the evacuation choice context.

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

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

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

2. Literature

2.1. Utility maximization and evacuation behavior

Discrete choice analysis is a modeling technique that uses discrete variables of the decision-maker or alternatives to predict choice (see Ben-Akiva et al., 1985; Train, 2009 for overviews). Most techniques in these reviews use utility maximization as the primary decision rule, largely because its statistical properties produce relatively simple, accurate, and tractable solutions with a clear connection to welfare economics. The error-inclusive random utility maximization (RUM) model has been the primary behavioral model form across transportation choices, including evacuations. This has included hurricane evacuations (Zhang et al., 2004; Smith and McCarty, 2009; Huang et al., 2012; Murray-Tuite et al., 2012) and wildfire evacuations (Paveglio et al., 2014; McNeill et al., 2015). These studies leverage binary logit models to find factors – often demographics or risk perceptions – that influenced decision making. Other modeled hurricane evacuation choices include transportation mode (Deka and Carnegie (2010), shelter type (Smith and McCarty, 2009; Deka and Carnegie (2010), and route (Akbarzadeh and Wilmot, 2015). Wong et al. (2018) reviews hurricane evacuation behavioral modeling and developed RUM models for evacuation choices. Other hurricane evacuation work has extended these models by employing different distributions through a probit model (Solís et al., 2010), creating choice nesting structures through a nested logit (Mesa-Arango et al., 2013), including random parameters through a mixed logit (Sadri et al., 2014; Sarwar et al., 2018), developing dynamic models through a sequential logit (Fu and Wilmot, 2004; Fu et al., 2006), considering decisions as multi-dimensional and joint (Wong et al., 2020) or accounting for different lifestyle preferences through a latent class choice model for tsunamis (Urata and Pel, 2018) and wildfires (McCaffrey et al., 2018). Despite this work, models continue to focus on demographic variables, risk perceptions, or hazard characteristics, not choice attributes.

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

2.2. Random regret minimization (RRM)

To handle the limitations of linear-in-parameters utility maximization models, researchers have developed other decision rules, such as regret minimization. Regret minimization (and the error-inclusive random regret minimization) approach takes the theoretical concepts of regret theory (Loomes and Sugden, 1982) and statistical techniques in discrete choice (Ben-Akiva et al., 1985) to develop a model for multinomial choice sets and multiple attributes in risky or riskless situations (Chorus et al., 2008; Chorus, 2010). Regret minimization models

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

Authors (Year)	Wildfire(s)	Key Location(s)	N	Model Type	Wildfire Choice
Mozumder et al. (2008)	Hypothetical	East Mountain, Albuquerque, New Mexico	1018	Binary Probit	Evacuate or Stay/Defend
Paveglio et al. (2014)	Hypothetical	Flathead County, Montana	734	Multinomial Logit	Evacuate or Stay/Defend
McNeill et al. (2015)	Hypothetical	Western Australia	182	Multinomial Logit	Evacuate or Stay/Defend + Delayed Response
Strahan (2017)	Perth Hills Bushfire (2014); Adelaide Hills Bushfire (2015)	Perth Hills, Australia; Adelaide Hills, Australia	429	Binary Logit	Evacuate or Stay/Defend
McCaffrey et al. (2018)	Sample of respondents from different regions with different fire contexts	Horry County, South Carolina; Chelan County, Washington; Montgomery County, Texas	759	Multinomial Logit + Latent Class	Evacuate or Stay/Defend
Toledo et al. (2018)	Haifa Wildfire (2016)	Haifa, Israel	516	Binary Logit	Evacuate or Stay/Defend

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

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

- In about one-third of cases (data-sets, applications), RUM models outperform RRM in model fit and out-of-sample predictions. For the remaining (roughly) two-thirds of cases, models that allow one or more attributes to be processed using RRM-principles perform better. In about half of these cases, a model that presumes RRM for every attribute does best.
- The conventional RRM model (Chorus, 2010) can only generate limited levels of regret aversion and modest potential improvements of model fit. Predictive performance over linear RUM models are generally small. The μRRM model (van Cranenburgh et al., 2015) can capture more extreme levels of regret aversion, leading to potentially large differences in empirical performance compared to RUM models.

2.3. RRM and revealed preference

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

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

Some studies have attempted to tackle these challenges. Using RP data on parking choice, Chorus (2010) estimated both RRM and RUM models by asking participants to provide attributes of other parking facilities that they used around campus. Boeri et al. (2012) used a RP survey, where participants rated on a Likert scale from 1 to 5 on variables associated with kayaking sites, but only those they had visited. Similarly, for mode choice, Parthan and Srinivasan (2013) used a Likert scale from 1 to 5 for attributes for chosen and non-chosen modes, finding regret tended to perform better for most mode choice attributes.

Prato (2014) estimated RRM and RUM models for route choice using collected data from commuters. The choice set was constructed using a branch and bound algorithm, building two to 19 additional alternatives. Sharma et al. (2019) also used RP data for park-and-ride lot choice. Given a finite number of lots, the research constructed choice sets by imposing several distance constraints to identify alternatives.

2.4. Regret in evacuee behavior

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

2.5. Key research gaps

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

3. Methodology

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

3.1. RP survey methodology for RRM and RUM

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

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

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

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

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

In this methodology, we did not force responses for the first and second considered alternatives. If a respondent did not consider a first and/or second alternative, they could skip these sections. Moreover, if a respondent did not have an opinion of the attribute of an alternative, they could leave that attribute blank. This survey design was intended to give respondents the most freedom and not constrain answers to

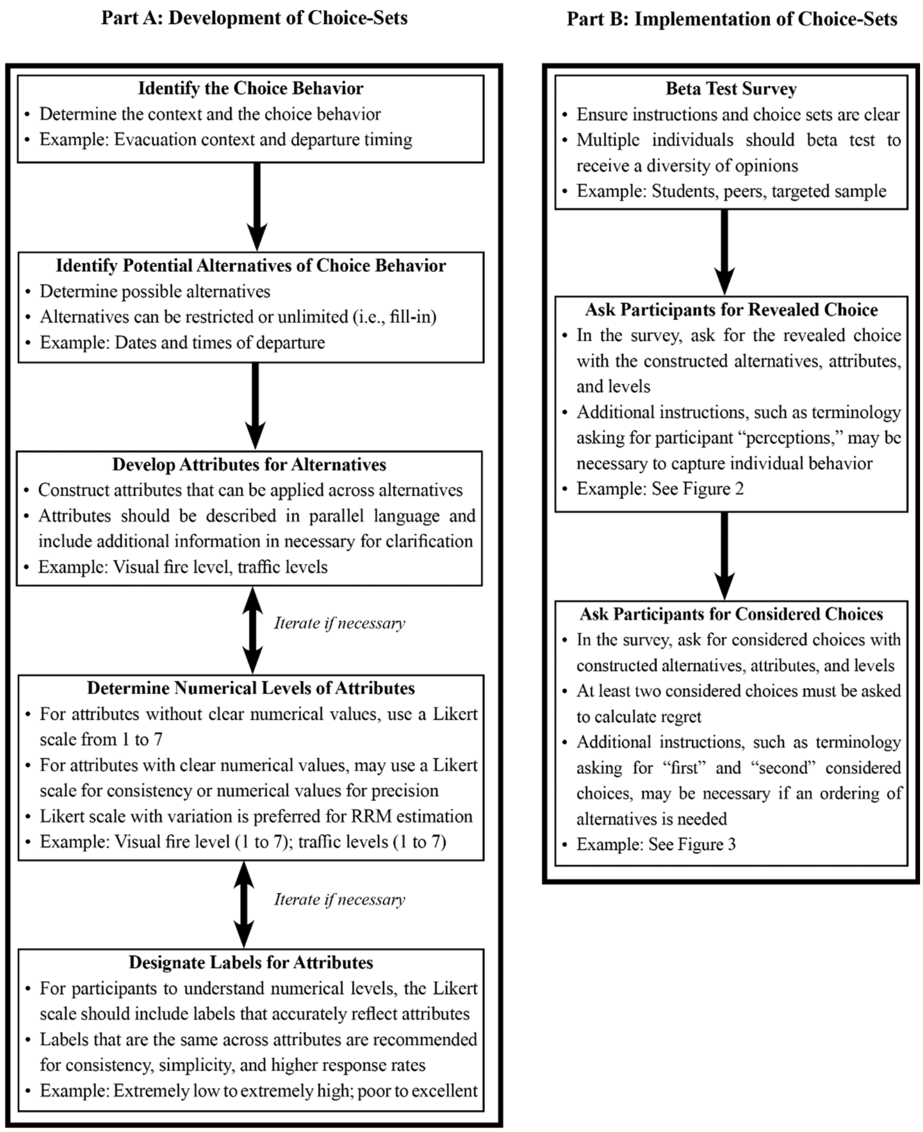

Fig. 1. RP Survey Methodology for RUM and RRM Models.

merely suit modeling needs. We did not include an option that explicitly stated that the respondent did not consider any other alternatives, which is a limitation of the survey design.

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

3.2. Survey distribution

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

For distribution, we compiled a list of local agencies, community-based organizations (CBOs), non-governmental organizations (NGOs), and news media organizations in the areas impacted by the wildfires.

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

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

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

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

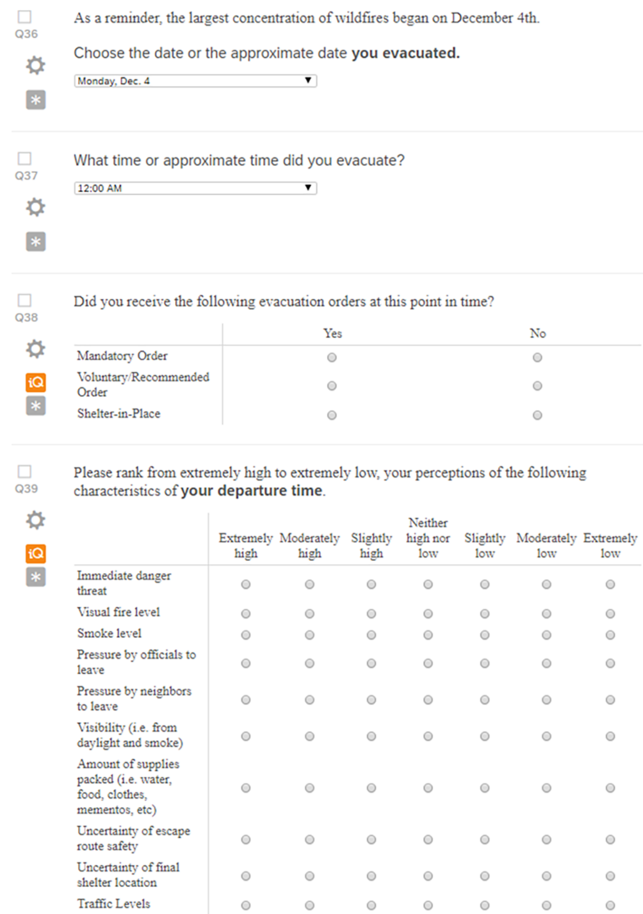

Fig. 2. Screenshot of Survey Design for Revealed Departure Time.

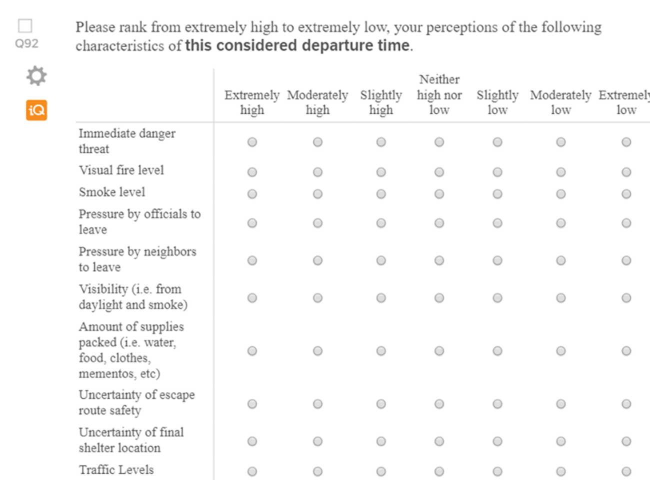

Fig. 3. Screenshot of Survey Design for Considered Departure Time.

3.3. RRM formulation

For RRM formulation, we followed the methodology from Chorus (2010) for the classical RRM (CRRM) model, Van Cranenburgh et al.

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

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

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

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

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

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

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

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

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

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

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

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

$$P^\mu_i = \frac{\exp(-R^\mu_i)}{\sum_{j=1 \ldots J} \exp(-R^\mu_j)} \tag{6}$$

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

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

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

Individual Characteristics (n = 226)			
Gender		**Employment**	
Male	26.1%	Employed full time	57.1%
Female	73.9%	Employed part time	11.9%
		Unemployed looking for work	4.9%
Age		Retired	22.1%
18–24	2.7%	Student	2.2%
25–34	17.7%	Disabled	1.3%
35–44	15.0%	Prefer not to answer	0.4%
45–54	19.0%		
55–64	26.5%	**Primary Transportation Mode for Work/School**	
65+	19.0%	Drive alone using a car, SUV, pickup, or van	87.6%
		Carpool/vanpool	2.2%
Race		Rail (e.g., light/heavy, subway/metro, trolley)	0.9%
Asian	2.7%	Bus	1.8%
Black or African-American	0.4%	Motorcycle/scooter	0.9%
Mixed	7.5%	Bicycle	0.9%
Native American/Alaska Native	0.4%	Walk	0.4%
Pacific Islander	0.9%	Work from home	1.8%
White	81.4%	Other	0.9%
Other	4.0%	Prefer not to answer/No answer	2.7%
Prefer not to answer	2.7%		
		Previous Evacuee[*]	
Ethnicity		Yes	35.3%
Hispanic	11.1%	No	64.7%
Not Hispanic	76.1%		
Prefer not to answer	12.8%	**Previous Wildfire Experience**[**]	
		Yes	93.4%
Education		No	6.6%
Less than high school	0.0%		
High school graduate	0.9%	**Mobile Phone Type**	
Some college	15.9%	Do not own a mobile phone	2.7%
2-year degree	5.8%	Own a typical mobile phone (non-smartphone)	5.3%
4-year degree	41.2%	Own a smartphone	92.0%
Professional degree	28.3%		
Doctorate	8.0%	**In-Vehicle or Smartphone Navigation**[***]	
Prefer not to answer	0.0%	Yes	79.6%
		No	20.4%
Household Characteristics (n = 226)			
Current County of Residence		**Home Ownership**[†]	
Ventura	43.8%	Yes	67.3%
Santa Barbara	41.6%	No	29.6%
Los Angeles	13.3%	Prefer not to answer	3.1%
Other California	1.3%		
		Live in Cal Fire High Risk Area[††]	
Displacement after Wildfire		Yes	38.1%
Same Residence	88.9%	No	28.8%
Different Residence or Not Returned	10.6%	I don't know	33.2%
No answer	0.4%		
		Current Household Characteristics	
Length of Residence[†]		Household with Disabled	14.2%
<6 months	5.8%	Household with Children	25.2%
6–11 months	4.9%	Household with Older Adults	28.3%
1–2 years	12.4%	Households with Pets	63.7%
3–4 years	14.6%		
5–6 years	7.1%	**Household Income (2017)**	
7–8 years	5.3%	Less than $10,000	0.4%
9–10 years	4.9%	$10,000–$14,999	1.3%
More than 10 years	45.1%	$15,000–$24,999	2.2%
		$25,000–$34,999	2.2%
Residence Structure[†]		$35,000–$49,999	6.2%
Site build (single home)	73.9%	$50,000–$74,999	14.6%

(continued on next page)

Table 3 (*continued*)

Household Characteristics (n = 226)			
Site build (apartment)	19.5%	$75,000–$99,999	11.5%
Mobile/manufactured home	6.2%	$100,000–$149,999	21.2%
Prefer not to answer	0.4%	$150,000–$199,999	13.3%
		$200,000 or more	14.2%
		Prefer not to answer	12.8%
Evacuation Choices (n = 175)			
Evacuation Choice (n = 226)		**Usage of GPS for Routing**	
Evacuated	77.4%	Yes, and followed route	18.3%
Did Not Evacuate	22.6%	Yes, but rarely followed route	4.6%
		No	77.1%
Departure Date			
Monday, Dec. 4	32.6%	**Multiple Destinations**	
Tuesday, Dec. 5	28.6%	Sheltered in more than one location	41.7%
Wednesday, Dec. 6	5.1%	Sheltered in one location	58.3%
Thursday, Dec. 7	4.0%		
Friday, Dec. 8	4.6%	**Within County Evacuation**	
Saturday, Dec. 9	3.4%	Yes	66.3%
Sunday, Dec. 10	8.0%	No	33.7%
After Sunday, Dec. 10	13.7%		
		Mode Choice	
Departure Timing by Hour		One personal vehicle	45.1%
12:00 AM – 5:59 AM	23.4%	Two personal vehicles	40.6%
6:00 AM – 11:59 AM	24.6%	More than two personal vehicles	8.6%
12:00 PM – 5:59 PM	24.6%	Aircraft	0.6%
6:00 PM – 11:59 PM	27.4%	Rental car	0.6%
		Recreational vehicle (RV)	1.1%
Shelter Type		Truck and trailer	2.3%
A friend's residence	30.3%	Non-household carpool	1.1%
A family member's residence	32.6%		
A hotel or motel	22.9%	**Reentry Date**	
A public shelter	3.4%	Tuesday, Dec. 5	4.9%
A second residence	2.9%	Wednesday, Dec. 6	9.9%
A portable vehicle (e.g., RV)	4.0%	Thursday, Dec. 7	4.9%
Peer-to-peer service (e.g., Airbnb)	1.1%	Friday, Dec. 8	11.7%
Other	2.9%	Saturday, Dec. 9	8.0%
		Sunday, Dec. 10	6.2%
Primary Route by Road Type		Monday, Dec. 11	4.3%
Highways	62.3%	Tuesday, Dec. 12	3.1%
Major Roads	15.4%	Wednesday, Dec. 13	3.1%
Local Roads	4.0%	Thursday, Dec. 14	3.7%
Rural Roads	1.1%	Friday, Dec. 15	2.5%
No Majority Type	17.1%	Saturday, Dec. 16	1.2%
		Sunday, Dec. 17	4.3%
		After Sunday, Dec. 17	32.1%

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

* "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.

4. Results and discussion

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

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

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

4.1. Departure timing choice

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

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

	Full RUM Model				CRRM Model				uRRM Model				Attribute-Specific uRRM Model			
	Coef.	Std. Error	p-value		Coef.	Std. Error	p-value		Coef.	Std. Error	p-value		Coef.	Std. Error	p-value	
Immediate Danger Threat	−0.57	0.16	<0.01	***	−0.32	0.10	<0.01	***	−0.38	0.11	<0.01	***	−0.37	0.11	<0.01	***
Pressure from Neighbors to Leave	0.43	0.14	<0.01	***	0.28	0.09	<0.01	***	0.29	0.09	<0.01	***	0.29	0.09	<0.01	***
Pressure from Officials to Leave	0.13	0.10	0.19		0.07	0.06	0.25		0.09	0.07	0.19		0.08	0.07	0.20	
Uncertainty of Escape Route	−0.27	0.11	0.01	**	−0.16	0.06	0.01	**	−0.18	0.07	0.01	**	−0.18	0.07	0.01	**
Smoke Level	0.20	0.18	0.28		0.13	0.11	0.26		0.13	0.12	0.28		0.14	0.12	0.27	
Amount of Supplies Packed (i.e., water, food, clothes, mementos)	0.01	0.10	0.92		0.02	0.06	0.80		0.01	0.07	0.92		0.01	0.07	0.91	
Traffic Levels	−0.16	0.12	0.19		−0.09	0.07	0.20		−0.11	0.08	0.19		−0.11	0.08	0.19	
Visibility (i.e., from daylight and smoke)	0.24	0.12	0.04	*	0.13	0.07	0.06	†	0.16	0.08	0.04	*	0.16	0.08	0.04	*
Visual Fire Level	0.50	0.19	0.01	**	0.29	0.12	0.01	**	0.33	0.13	0.01	**	0.33	0.13	0.01	**
mu (generic across attributes)									≫10.00	≫10.00	0.95					
mu Visual Fire Level													2.23	13.8	0.87	
Final log likelihood:	−103.6				−105.7				−103.6				−103.8			
Rho-square:	0.19				0.18				0.19				0.19			
Adjusted rho-square:	0.12				0.11				0.12				0.12			

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

4.2. Route choice

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

4.3. Shelter choice

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

4.4. Transportation mode choice

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

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

Route Choice (n = 93)	Full RUM Model				CRRM Model				uRRM Model				Attribute-Specific uRRM Model			
	Coef.	Std. Error	p-value		Coef.	Std. Error	p-value		Coef.	Std. Error	p-value		Coef.	Std. Error	p-value	
Difficulty in Driving (i.e., hilly, winding)	−0.12	0.11	0.26		−0.08	0.07	0.23		−0.08	0.07	0.26		−0.08	0.07	0.24	
Distance of Route	−0.33	0.13	0.01	**	−0.19	0.08	0.01	**	−0.22	0.08	0.01	**	−0.22	0.08	0.01	**
Prior Experience with Route	0.16	0.13	0.20		0.11	0.09	0.20		0.11	0.08	0.20		0.11	0.08	0.19	
Fire Danger	−0.36	0.13	0.01	**	−0.24	0.09	0.01	**	−0.24	0.09	0.01	**	−0.25	0.09	0.01	**
First Responder Presence (i.e., fire, medical)	−0.45	0.30	0.13		−0.15	0.11	0.17		−0.30	0.20	0.13		−0.27	0.18	0.12	
Police Presence	0.16	0.31	0.59		−0.03	0.11	0.80		0.11	0.20	0.59		0.08	0.18	0.65	
Pavement Condition	0.49	0.16	<0.01	***	0.32	0.11	<0.01	***	0.33	0.11	<0.01	***	0.33	0.11	<0.01	***
mu (generic across attributes)									≫10.00	≫10.00	1.00					
mu Fire Danger													0.59	0.989	0.55	
Final log likelihood:	−76.0				−77.5				−76.0				−76.0			
Rho-square:	0.26				0.24				0.26				0.26			
Adjusted rho-square:	0.19				0.18				0.18				0.18			

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

4.5. Reentry timing choice

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

5. Limitations

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

Throughout the development of our RP survey methodology and analysis, we found several important limitations to our methodology,

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

Shelter Choice (n = 118)	Full RUM Model				CRRM Model				uRRM Model				Attribute-Specific uRRM Model (No Regret Found)			
	Coef.	Std. Error	p-value		Coef.	Std. Error	p-value		Coef.	Std. Error	p-value		Coef.	Std. Error	p-value	
Amenities	0.07	0.12	0.52		0.05	0.07	0.50		0.05	0.08	0.52		0.05	0.08	0.52	
Comfort	0.07	0.11	0.51		0.05	0.07	0.48		0.05	0.07	0.51		0.05	0.07	0.51	
Cost	−0.05	0.08	0.50		−0.04	0.05	0.45		−0.03	0.05	0.50		−0.03	0.05	0.50	
Distance Away	−0.11	0.09	0.21		−0.07	0.06	0.21		−0.07	0.06	0.21		−0.07	0.06	0.21	
Safety	0.35	0.12	<0.01	***	0.22	0.08	<0.01	***	0.23	0.08	<0.01	***	0.23	0.08	<0.01	***
Social Connections	0.11	0.09	0.20		0.07	0.05	0.20		0.07	0.06	0.20		0.07	0.06	0.20	
mu (generic across attributes)									≫10.00	≫10.00	0.95					
Final log likelihood:	−116.1				−116.4				−116.1				−116.2			
Rho-square:	0.10				0.10				0.10				0.10			
Adjusted rho-square:	0.06				0.06				0.05				0.06			

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

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

Mode Choice (n = 70)	Full RUM Model			CRRM Model			uRRM Model			Attribute-Specific uRRM Model (No Regret Found)		
	Coef.	Std. Error	p-value	Coef.	Std. Error	p-value	Coef.	Std. Error	p-value	Coef.	Std. Error	p-value
Availability	0.15	0.13	0.27	0.08	0.08	0.28	0.09	0.09	0.27	0.15	0.13	0.27
Cost	−0.12	0.12	0.32	−0.07	0.08	0.36	−0.08	0.08	0.32	−0.12	0.12	0.32
Safety	0.11	0.15	0.47	0.07	0.09	0.39	0.07	0.10	0.47	0.11	0.15	0.47
Speed	0.09	0.15	0.54	0.05	0.08	0.52	0.06	0.10	0.54	0.09	0.15	0.54
mu (generic across attributes)							≫10.00	≫10.00	1.00			
Final log likelihood:	−73.4			−73.6			−73.4			−73.34		
Rho-square:	0.05			0.04			0.05			0.05		
Adjusted rho-square:	−0.01			−0.01			−0.02			−0.01		

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

which should be addressed.

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

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

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

6. Recommendations

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

6.1. Methodological recommendations

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

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

Reentry Choice (n = 89)	Full RUM Model				CRRM Model				uRRM Model				Attribute-Specific uRRM Model			
	Coef.	Std. Error	p-value		Coef.	Std. Error	p-value		Coef.	Std. Error	p-value		Coef.	Std. Error	p-value	
Allowed to Return	0.23	0.12	0.04	*	0.17	0.08	0.04	*	0.16	0.08	0.04	*	0.18	0.09	0.04	*
Concerns of Fire Still Burning	−0.10	0.10	0.35		−0.05	0.07	0.42		−0.06	0.07	0.35		−0.06	0.07	0.37	
Cost of Current Shelter	0.13	0.11	0.24		0.07	0.07	0.26		0.09	0.07	0.24		0.09	0.07	0.21	
Need to Check on People	0.25	0.15	0.08	†	0.16	0.09	0.10	†	0.17	0.10	0.08	†	0.17	0.10	0.08	†
Need to Check Residence	0.22	0.18	0.24		0.14	0.12	0.25		0.14	0.12	0.24		0.14	0.12	0.27	
Comfort of Current Shelter	−0.18	0.13	0.15		−0.10	0.08	0.19		−0.12	0.08	0.15		−0.12	0.08	0.16	
Confidence of Power Availability	0.01	0.15	0.93		0.01	0.11	0.91		0.01	0.10	0.93		0.01	0.11	0.96	
Pressure to Return to Job/Work	0.03	0.17	0.86		0.01	0.10	0.91		0.02	0.11	0.86		0.02	0.11	0.86	
mu (generic across attribute)									≫10.00	≫10.00	0.98					
mu Allowed to Return													0.31	0.49	0.53	
mu Pressure to Return to Job/Work													1.65	31.00	0.96	
Final log likelihood:	−86.8				−87.2				−86.9				−86.6			
Rho-square:	0.11				0.11				0.11				0.11			
Adjusted rho-square:	0.03				0.03				0.02				0.01			

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

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

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

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

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

Of these recommendations, the most drastic is developing an SP survey. While we acknowledge that SP surveys are not well-suited for unrealistic situations, we also realize that RP survey implementation is hard. Moreover, large sample size, increased variation, and opt-out reduction for SP outweigh the limitations. The SP survey could be administered to evacuees by collecting data from individuals who recently made important and difficult evacuation decisions or non-evacuees who are at risk for a specific hazard. While the RP survey collects actual behavior, we recognize that determining the behavioral accuracy of regret minimization may require an SP survey for a hypothetical disaster, particularly to increase the sample size.

6.2. Policy recommendations

In addition to methodological improvements, we offer several policy recommendations for agencies to improve wildfire evacuation outcomes based on our analysis. We focus on significant variables for the RUM models, as we were unable to establish definitive proof of regret across choices. Consequently, we are unable to provide policy recommendations for mode choice. We also note that many of these recommendations are not innovative or surprising. However, we provide them to help build additional consensus of certain strategies for public

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

Mode (n = 70)	RUM Latent Class Model				uRRM Latent Class Model			
Class 1	Coef.	Std. Error	p-value		Coef.	Std. Error	p-value	
Availability	4.70	3.03	0.12		2.47	1.47	0.09	†
Cost	0.49	0.28	0.09	†	0.48	0.32	0.13	
Safety	−1.09	0.69	0.11		−0.37	0.29	0.20	
Speed	2.28	1.22	0.06	†	0.82	0.49	0.10	†
mu (generic across attributes)					≫10.00	≫10.00		
Class 2	Coef.	Std. Error	p-value		Coef.	Std. Error	p-value	
Availability	−2.50	1.61	0.12		−4.59	3.99	0.25	
Cost	−1.77	1.35	0.19		−1.56	1.18	0.19	
Safety	7.24	4.36	0.10	†	0.73	0.78	0.35	
Speed	−6.92	4.20	0.10	†	−0.05	0.58	0.93	
mu (generic across attributes)					2.50	4.20	0.55	
Percentage Class 1	63.1%				62.8%			
Percentage Class 2	36.9%				37.2%			
Final log likelihood:	−59.8				−60.9			
Rho-square:	0.22				0.21			
Adjusted rho-square:	0.11				0.06			

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

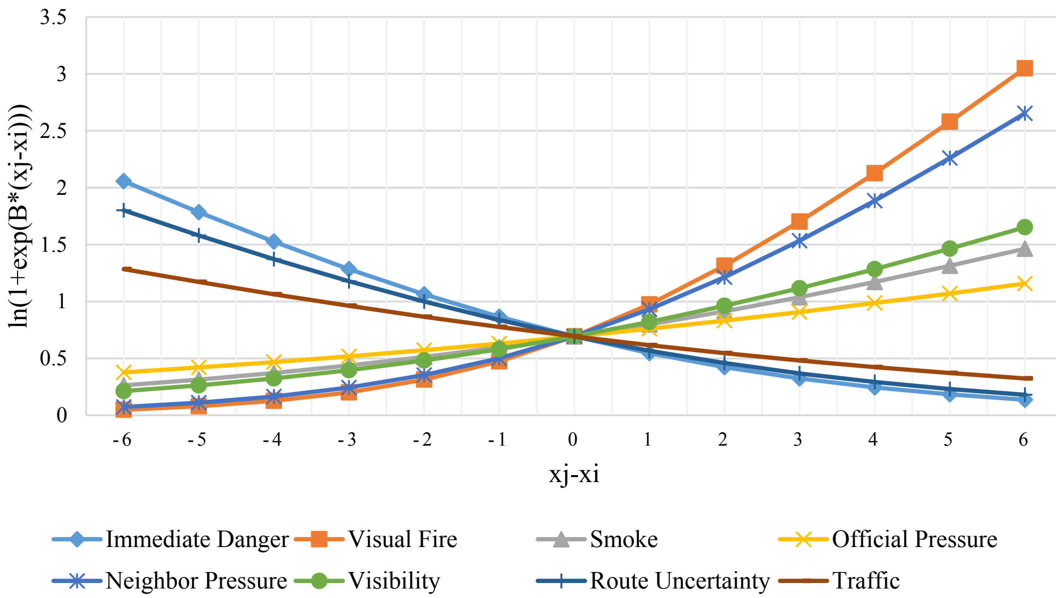

Fig. 4. Regret Functions for Departure Timing Example.

agencies, which is especially critical for wildfires (as opposed to highly studied hurricanes).

Recommendation 1: Agencies should encourage evacuees to leave before they visually see the fire. While the precise time to issue mandatory evacuation orders is highly dependent on the fire speed, wind, fuel loads, and geography, agencies should err on the side of caution to ensure that the slowest evacuees is able to leave. Alternatively, agencies could consider advanced trigger models (Li et al., 2019) that identify when officials should issue orders based on the fire and targeted evacuation clearance times.

Evidence: The departure timing model shows that evacuees chose a departure time when the visual fire was high (significant variable), indicating the importance of environmental cues. An earlier response – leaving when fire visibility is still low – should be encouraged by agencies to reduce later departures, which are riskier.

Recommendation 2: Agencies should increase evacuation information at the neighborhood level to leverage neighbor networks. Accurate evacuation information, particularly on planned departure times for a time-phased evacuation, should be distributed at a local level through different mechanisms (e.g., community-based organizations, Community Emergency Response Teams [CERTs], neighborhood associations).

Evidence: Evacuees were more likely to choose a specific departure time, if they experienced pressure from neighbors to leave (significant variable). Neighbors can play a beneficial role in providing useful information or negatively impact the evacuation by propagating rumors.

Recommendation 3: Agencies should provide clear routing information, including routes not overtaken by fire, to reduce route uncertainty. This may require coordination with other jurisdictions and routing applications (e.g., Waze, Google Maps) to dynamically route around blocked routes (e.g., due to debris). Moreover, agencies need to leverage low-tech forms of communication (e.g., radios), if power is lost or mobile phones do not have coverage.

Evidence: The departure time model shows that individuals were

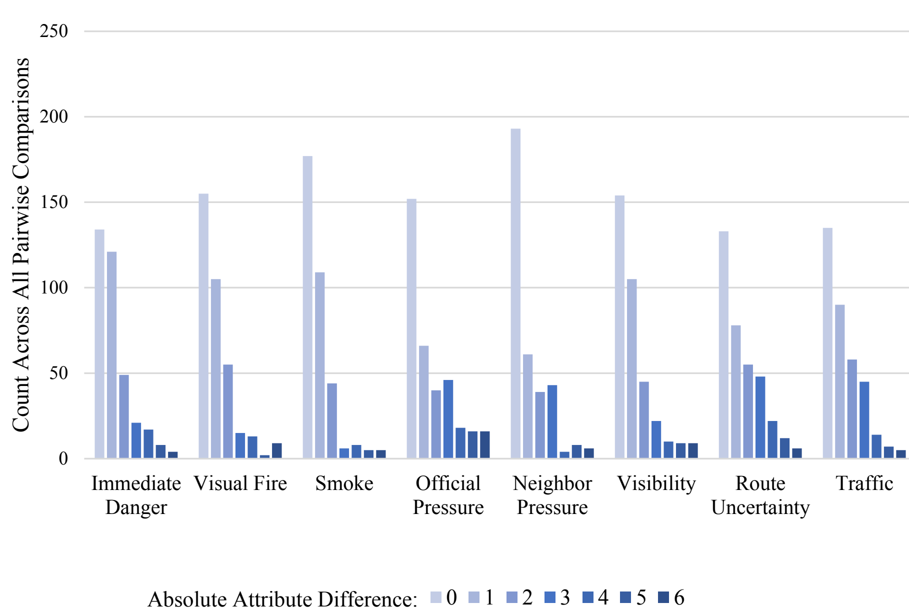

Fig. 5. Histogram of Absolute Attribute Differences Across All Pairwise Regret Comparisons for Departure Timing Example.

less likely to choose a departure time, if they were uncertain about their escape route (significant variable). This hesitation may cause more late departures, which places evacuees in higher danger. Moreover, the route choice model shows that people preferred routes with less fire danger (significant variable).

Recommendation 4: Agencies should prepare transportation operations at a highly localized level (as opposed to a multi-jurisdictional level) to reduce congestion. For example, agencies could implement signal priority, parking restrictions, and/or contraflow at critical intersections or along heavily used road links close to the wildfire impact area.

Evidence: Evacuees preferred routes that were short-distance (significant variable), and approximately two-thirds of evacuations occurred within the county (see Table 3). These results suggest that most evacuees preferred to remain close by but still outside of the evacuation zone. Naturally, this could lead to notable congestion in neighborhoods.

Recommendation 5: Agencies should pre-plan public shelters in areas with a low likelihood of fire danger (fire safety), ensure shelters are secure for all populations (personal safety), and provide necessary health supplies and resources (life safety). Since it is uncertain what areas and accommodations will be viable during a wildfire, agencies should establish a safe option for evacuees via public shelters.

Evidence: Evacuees chose shelters that were more likely to secure safety (significant variable). While the type of safety (e.g., fire, personal, life) could not be determined, the shelter choice model suggests that an improvement in safety (for example, a public shelter) would make it a more attractive option for evacuees (in contrast to more expensive hotels/motels).

7. Conclusions

In this paper, we developed a RP survey methodology to estimate both RUM and RRM models. We applied this methodology to a wildfire evacuation choice context that we hypothesized would exhibit regret-minimizing behavior, as opposed to traditional utility-maximizing behavior. Across multiple evacuation choices, we did not find support for this hypothesis, although weak and modest regret-aversion behavior was found for several specific attributes. We also found a class of weakly regret-averse behaviors for route and mode choice. Across all choices, the CRRM model had a poorer fit than the RUM model, which was confirmed by the μRRM model which revealed no or only modest regret aversion. We hypothesize that these results are largely due to poor attribute-level variation in the dataset.

Despite these results, future work on decision rules and evacuations should continue. Indeed, RRM models are heavily dependent on the choice set construction and the dataset. Future work should incorporate the methodological improvements to the RP survey for other disasters, including those beyond wildfires. Moreover, the RP survey methodology can be reproduced beyond the evacuation context (or even transportation context) to other choice situations. Due to limited attribute variation and RP weaknesses, we also recommend testing a SP survey with experienced evacuees and non-evacuees to identify possible regret. We conclude that further exploration of the RP survey methodology and regret testing, using both RP and SP, is needed before an adequate conclusion can reached for using the regret-minimizing tool for evacuation behavior.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Mixed-decision latent class choice model (MDLCCM) overview

While the CRRM and μRRM models assume that all respondents make decisions using the same decision rule, the MDLCCM allows for additional heterogeneity through the mixing of decision rules. This mixing is allowed through a latent class choice model (LCCM) as developed in Hess et al. (2012). Since an individual's decision rule is not observed, an LCCM is an intuitive method for representing mixtures of decision rules. In this model, individuals may belong to a class based on whether their decision rule is regret-based or utility-based. As explained in Hess et al. (2012), the difference across classes is a result of both different parameters and the assumed behavioral process. We first mention that choice probabilities for a choice y_i for utility or regret is now conditional on whether the individual belongs to a regret (r) or utility (u) class:

$$P(y_i|r) = \frac{\exp(-R_i)}{\sum_{j=1\ldots J}\exp(-R_j)} \quad (7)$$

$$P(y_i|u) = \frac{\exp(V_i)}{\sum_{j=1\ldots J}\exp(V_j)} \quad (8)$$

In the utility equation, V_i is the associated utility for alternative i. To account for the different decision rules and parameterizations associated with the regret- and utility-class, the probabilities for belonging to each class (expressed as π) are multiplied by the choice probability for the alternative under a given choice model.

$$P(y_i) = \pi_r P(y_i|r) + \pi_u P(y_i|u) \quad (9)$$

One item to mention is that we focus entirely on the class-specific model formulation. A clear extension of this is to develop a membership model, which could e.g. include socio-demographic and context-related factors. In addition, while this type of mixture-decision model works best with panel

Table A1
Construction of Choice Sets for Survey for Revealed Preference and Considered Alternatives.

Choice	RP Alternatives		Considered Alternatives
Departure Timing	*Date Options*	*Time of Day Options*	*Amount of Time Before or After Chosen Alternative*
	Monday, Dec. 4	12:00 AM	More than 1 day earlier
	Tuesday, Dec. 5	1:00 AM	1 day earlier
	Wednesday, Dec. 6	2:00 AM	12 hours earlier
	Thursday, Dec. 7	3:00 AM	6 hours earlier
	Friday, Dec. 8	4:00 AM	3 hours earlier
	Saturday, Dec. 9	5:00 AM	1 hour earlier
	Sunday, Dec. 10	6:00 AM	Less than 1 hour earlier
	Monday, Dec. 11	7:00 AM	Less than 1 hour later
	Tuesday, Dec. 12	8:00 AM	1 hour later
	Wednesday, Dec. 13	9:00 AM	3 hours later
	Thursday, Dec. 14	10:00 AM	6 hours later
	Friday, Dec. 15	11:00 AM	12 hours later
	Saturday, Dec. 16	12:00 PM	1 day later
	Sunday, Dec. 17	1:00 PM	More than 1 day later
	Monday, Dec. 18	2:00 PM	
	Tuesday, Dec. 19	3:00 PM	
	Wednesday, Dec. 20	4:00 PM	
	Thursday, Dec. 21	5:00 PM	
	Friday, Dec. 22	6:00 PM	
	Saturday, Dec. 23	7:00 PM	
	Sunday, Dec. 24	8:00 PM	
	After Sunday, Dec. 24	9:00 PM	
		10:00 PM	
		11:00 PM	
Route	*Route Options*		*Route Options*
	Fill-in of main roads in order (e.g., Spruce Drive, Harrison Parkway, Highway 101, Interstate 405)		Fill-in of main roads in order (e.g., Spruce Drive, Harrison Parkway, Highway 101, Interstate 405)
Mode	*Mode Options*		*Mode Options*
	One personal vehicle		One personal vehicle
	Two personal vehicles		Two personal vehicles
	More than two personal vehicles		More than two personal vehicles
	Carpool/vanpool with non-household people		Carpool/vanpool with non-household people
	Shuttle service		Shuttle service
	Ridesourcing/TNC (e.g., Uber, Lyft)		Ridesourcing/TNC (e.g., Uber, Lyft)
	Microtransit (e.g., Via)		Microtransit (e.g., Via)
	Carsharing (e.g., Zipcar, GIG Car Share)		Carsharing (e.g., Zipcar, GIG Car Share)
	Rental car		Rental car
	Rail (e.g., light/heavy, subway/metro, trolley)		Rail (e.g., light/heavy, subway/metro, trolley)
	Bus		Bus
	Walk		Walk
	Motorcycle/scooter		Motorcycle/scooter
	Bicycle		Bicycle
	Aircraft		Aircraft
	Recreational vehicle (RV)		Recreational vehicle (RV)
	Other		Other
Shelter Type	*Shelter Options*		*Shelter Options*
	A friend's residence		A friend's residence
	A family member's residence		A family member's residence
	A hotel or motel		A hotel or motel
	A second residence		A second residence
	A public shelter		A public shelter
	Any shelter found through a peer-to-peer service (e.g., Airbnb)		Any shelter found through a peer-to-peer service (e.g., Airbnb)
	A portable vehicle (e.g., automobile, camper, RV)		A portable vehicle (e.g., automobile, camper, RV)
	Other		Other
Reentry	*Reentry Options*		*Amount of Time Before or After Chosen Alternative*
	Any date after and including Dec. 4		More than 7 days earlier
			5-7 days earlier
			3-4 days earlier
			2 days earlier
			1 day earlier
			Less than 1 day earlier
			Less than 1 day later
			1 day later
			2 days later
			3-4 days later
			5-7 days later
			More than 7 days later

data (i.e., where the same respondent makes multiple choices), its use for a single choice remains viable.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tbs.2020.04.003.

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