

RESEARCH ARTICLE



A comparison of attribute non-attendance in online and mail choice experiment surveys for eliciting Colorado homeowners values for reducing wildfire risks

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ABSTRACT

Although there have been several contingent valuation studies comparing online and mail surveys, only a few comparative studies have been conducted using choice experiments (CE). CEs portray each choice option as different levels of attributes. The assumption is that survey respondents make trade-offs between attribute levels when making their choices among alternative options. Recent research has demonstrated that respondents do not always pay attention to *all* attributes when making choices. Methods have been developed to estimate attribute non-attendance (AN-A) and its influence on willingness to pay (WTP). This study provides the first comparison of WTP values for environmental programmes obtained from online versus mail CE surveys in which the impact of AN-A is evaluated. A CE survey of homeowners was conducted to estimate homeowner WTP for alternative programmes that reduce wildfire risk and damage to their home relative to a status quo alternative. Using the equality-constrained latent class model to infer AN-A, we found that AN-A noticeably increased goodness of fit in both mail and online samples compared with multinomial logit and random parameter logit models. WTP results are substantially lower when accounting for AN-A.

KEY POLICY HIGHLIGHTS

- Survey modes (mail and online) had comparable overall response rates, suggesting that online surveys are a cost-effective option to collect data from homeowners.
- Respondents to online surveys were generally younger, more affluent and had completed more years of education relative to mail survey respondents.
- Homeowners simplify choices among alternative wildfire risk mitigation programmes by ignoring some information. Accounting for this results in lower wildfire risk mitigation value estimates.
- Across both survey modes and all econometric models, retired homeowners held negative values for wildfire risk mitigation programmes, while homeowners with a bachelor's degree placed the highest value on such programmes.

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1. Introduction

The convergent validity of economic welfare estimates obtained using alternative stated preference survey modes remains an important research question. During the past two decades, several studies have compared the results of online surveys with other survey modes and reported significantly different willingness to pay (WTP) values (Boyle et al. 2016; Mjelde, Kim, and Lee 2016; Watson et al. 2019), while other found no difference (Balcombe et al. 2014; Campbell, Venn, and Anderson 2018; Olsen 2009; Windle and Rolfe 2011). Much of the earlier literature focused on comparisons between survey modes in contingent valuation surveys. However, there is growing popularity of stated preference choice experiment (CE) methods, in which respondents choose between mutually exclusive alternatives that differ across various characteristics and include a monetary attribute. As noted in our Literature Review section, there are fewer comparisons of the effect of survey mode in CE studies than in contingent valuation studies. Of these comparative CE studies, mixed results have been found with regard to survey response rates and WTP estimates (see below). This paper contributes to the literature by examining one possible explanation for divergence in value estimates across CE survey modes by accounting for attribute non-attendance and its influence on WTP estimates. To our knowledge, this is the first study to investigate the role that attribute non-attendance (AN-A) plays in a CE implemented across different survey modes.

The context of the current study concerns wildfire risk in Colorado, a state that has experienced significant loss of life and property from wildfires during the past decade. People often struggle to understand the concepts of risk and probability in the abstract, and risk variables have rarely been included in environmental economic CE studies. However, decisions regarding wildfire mitigation measures that can be taken by homeowners and communities involve trade-offs between the cost and benefit of mitigation actions (Bayham et al. 2022), and only a few previous studies have empirically investigated wildfire risk-loss-cost trade-offs (e.g. Holmes et al. 2013; Sánchez et al. 2022).¹ Decisions requiring individuals to weigh the importance of risk, expected loss and other factors are complex and have been found to induce the use of heuristics, such as ignoring or ‘non-attendance’ to some attributes of a choice experiment (Alho 2017).² Therefore, the motivation for this study is to compare the impact of AN-A on mail and online survey modes using a CE design focusing on risk-loss-cost trade-offs under two alternative wildfire mitigation programmes.

The paper proceeds as follows: first, we review the literature concerning survey mode comparisons on choice experiments and AN-A impacts on WTP values. This is followed by a presentation of the choice experiment survey design, which investigated homeowner preferences for private and public wildfire risk reduction activities and the survey modes used for data collection. Then the econometric models used for data analysis are described, followed by a comparison of the econometric results and estimates of WTP for the different survey modes. We then present comparative results on AN-A for the two different survey modes for our two fuel reduction programmes. Finally, we present our conclusions.

2. Literature review

As the internet has become more reliable and available to more people, especially in urban areas, online surveys are becoming increasingly popular based on the growing research on online survey methodology (Couper 2000; Dillman, Smyth, and Christian 2014; Shin, Johnson, and Rao 2012). In 2017, online surveys accounted for the majority of all quantitative survey modes (Daikeler, Bošnjak, and Lozar Manfreda 2020; ESOMAR 2018). Furthermore, the 2020 U.S. Census began offering the survey via online mode.³ In general, online surveys provide an advantage over traditional mail surveys in that they can collect data faster and at lower cost (Couper 2000; Dillman, Smyth, and Christian 2014; Fricker and Schonlau 2002; Nayak and Naraya 2019; Windle and Rolfe 2011). However, it is important to consider how online choice experiment surveys perform in terms of sample

coverage of the population of interest and survey response rate. Both sample coverage and survey response rate are important issues when survey results are extrapolated to the target population, as results may be biased if the sample is not representative of the overall population.

The probability of coverage and sampling errors increases for internet surveys if members of the target population (e.g. homeowners) are excluded from the sampling frame due to lack of internet access, in particular, those individuals who live in rural communities. This is an important concern in our study as wildfire risk is typically greater within the Wildland Urban Interface (WUI) where there continue to be areas with little or slow internet connectivity. Specifically, the Federal Communications Commission estimates that about 28% of those living in rural areas, e.g. the wildland aspect of WUI, have broadband access.⁴ This suggests that sample coverage in WUI areas may be higher with mail surveys than reliance on online surveys.

The evidence regarding internet survey response rates in choice experiment surveys is mixed. Some authors find no difference between internet and mail surveys (Olsen 2009), while others find either much lower (Campbell, Venn, and Anderson 2018; Shih and Fan 2009) or noticeably higher (Boyle et al. 2016) response rates for internet surveys.

A recent trend with online surveys has been the rise in fraudulent responses (e.g. automated responses-bots). This is happening at a higher rate when researchers disseminate surveys via email, social media and panels. A recent study reported that two online surveys had fraudulent response rates of 96% and 72% (Goodrich et al. 2023). For our study, we minimize fraudulent responses by initially reaching out to potential participants via phone, then randomly assigning households to mail or online and then collecting home addresses to mail a survey booklet or email addresses to send a link to an online survey to the respective subsamples.

Of particular importance to economic analysis is whether the resulting estimates of dollar values (e.g. willingness to pay – WTP) for the attributes or programmes vary by survey mode. Olsen (2009) found no difference in WTP values for protecting different landscapes from road encroachment across internet and mail samples in a CE study. Windle and Rolfe (2011) also report no difference between online and paper-based surveys for household WTP for environmental improvements in Australia's Greater Barrier Reef. A study by Campbell, Venn, and Anderson (2018) found that there is no significant difference in WTP estimates for woody biomass energy in Arizona, Colorado and Montana between several survey modes, which include online and mail surveys. Similarly, Balcombe et al. (2014) found that the WTP results are not impacted by the survey delivery (online vs mail), while Determann et al. (2017) found minor differences in WTP. However, other studies have found that survey modes have an influence on welfare estimates. For example, Boyle et al. (2016) found that, on average, respondents from a commercial internet panel who filled out survey responses online had monetary benefit estimates of about three-quarters of the mail estimates. Watson et al. (2019) found that WTP estimates for pharmacy services differ across survey modes (mail, online, computer-assisted personal interviews), in which mail surveys have higher WTP and online surveys the lowest values.

In this paper, we investigate whether differences in WTP across survey modes in a CE could result from AN-A behaviour based on inferred non-attendance. To our knowledge, this paper provides the first test of this hypothesis when comparing online and mail surveys. AN-A occurs when survey respondents ignore one or more attributes in the choice set questions (Hensher, Rose, and Greene 2005; Hess and Hensher 2010; Scarpa et al. 2013). There are two types of AN-A approaches: inferred and stated (Lew and Whitehead 2020). The inferred AN-A approach uses an econometric model to probabilistically discern AN-A behaviour, while in the stated approach, survey respondents provide self-reported information on attributes they ignore. Estimating marginal WTP with CE data where respondents ignore one or more attributes may lead to biased results (Scarpa et al. 2009). One way to model AN-A is to constrain coefficients to zero in a latent class framework (Scarpa et al. 2009). However, others have suggested that respondents do not fully ignore attributes, but rather place a lower importance on them, in which case may not be zero (Balcombe et al. 2014; Hess et al. 2013).

Glenk et al. (2015) compared equality-constrained latent class (ECLC) models used to infer AN-A to mixed logit models and found that ECLC models significantly reduced errors for marginal and total WTP estimates. Using similar model comparisons, Li and Ando (2023) found that average marginal WTP estimates fall by 38%–49% after accounting for AN-A behaviour. However, Petrolia and Hwang (2020) found that AN-A does not always improve model fit, but when it does, the method produces more precise WTP estimates. Other studies have found that accounting for AN-A results in an increase in WTP (Caputo et al. 2018; Scarpa, Thiene, and Hensher 2010), while others found a decrease (Hensher, Rose, and Greene 2005; Hindsley et al. 2023; Scarpa et al. 2013).

There is no research we are aware of comparing online and mail survey modes in choice experiments in the case of risk to property from natural hazards such as wildfires. In this paper, a comparison is made of results from a choice experiment using two household survey data collection modes. In addition, we account for AN-A behaviour by comparing model fit and marginal WTP estimates using standard multinomial logit (MNL), random parameter logit (RPL), AN-A inferred approach and latent class random parameter logit attribute non-attendance (LCRPL AN-A) models. This study will fill this literature gap by providing a study that compares online and mail survey modes for WTP estimates for fire mitigation programmes for the state of Colorado. The results likely will have implications for choice modelling of risks from other natural hazards such as floods and landslides.

Five hypothesis tests were used to compare online and mail surveys: (1) respondent characteristics; (2) survey response rates; (3) signs and significance of coefficients in the MNL, RPL and LCRPL AN-A models versus AN-A; (4) evaluation and comparison of model fits between AN-A, LCRPL AN-A, RPL and MNL models and (5) WTP estimates. Results of the study can fill a gap in the existing literature on survey mode effects by comparing an online sample to a traditional mail sample in a CE and accounting for AN-A behaviour. Furthermore, if online surveys produce similar results to mail surveys, relying solely on online surveys for future studies can help reduce the overall survey cost and speed up data collection.

3. Choice experiment survey design and survey mode comparisons

The choice experiment study in this paper adapted a survey previously developed for Florida homeowners (Holmes et al. 2013). The previous study was implemented using a mail survey. However, for this study, we conducted a split-sample mode, mail and online surveys for the state of Colorado during 2016–2017. Identical surveys were used in the two survey modes with random assignment of households to survey modes. This paper tests the hypotheses that both survey modes yield statistically insignificant differences between respondent characteristics, coefficients in the MNL, RPL and AN-A econometric models and WTP. To help determine whether AN-A behaviour is present in the choice experiment, we use the ECLC model described by Scarpa et al. (2009). This model probabilistically assigns respondents to latent classes with zero utility weights for specific attributes that are not attended to. Non-zero utility weights are assumed to take the same value across all classes as in the MNL model. Akaike and Bayesian information criteria (i.e. AIC and BIC) are used to evaluate and compare model fit. A more complex AN-A model was also used, LCRPL AN-A (Hess et al. 2013), in which the coefficients not fixed to zero (attend to attribute) are treated as random parameters to help capture random heterogeneity.

The overall survey portrays potential monetary damages to respondents' homes and property in terms of expected losses (based upon risk and monetary damages) under alternative community (public) and homeowner (private) wildfire risk mitigation scenarios such as forest thinning and prescribed fires. To start with, respondents are asked a series of questions about the existing vegetation throughout their neighbourhood and their individual home in order to prompt homeowners to think about potential fuel loads where they live. This is followed by descriptions of what

High Fire Risk Landscaping

High Fire Risk Landscaping: Wildfire experts in Colorado have determined that your home is at a **high risk** of being damaged by wildfire if most of the following are present around your home and in your neighborhood:

- A thick bed of pine needles on the ground (this carries fire across the ground)
- A continuous layer of highly flammable shrubs over 3 feet tall such as hedges (fire climbs into the trees)
- Vines and small trees underneath taller trees (fire climbs into the trees)
- Several (6 or more) trees within 30 feet of your house, and a few trees (1-5) touching or extending over your home (trees can carry fire to the roof)
- Dense vegetation blocking the view of your home from the street
- Dense, difficult to walk through areas of forest within ½ mile of your home

Medium Fire Risk Landscaping

Medium Fire Risk Landscaping: Your home would be at a **medium risk** of being damaged by a wildfire if most of the following characteristics are present:

- Unmowed or tall grass, weeds or small shrubs, and fine bark as mulch
- A few (1-5) highly flammable shrubs over 3 feet tall
- No vines or small trees underneath taller trees
- 1 to 5 trees within 30 feet of your house; none touch the house or over the roof
- A partial view of your home from the street
- Easy to walk through areas of forest within ½ mile of your home

Low Fire Risk Landscaping

Low Fire Risk Landscaping: Your home would be at a **low risk** of being damaged by wildfire if most of the following characteristics are present:

- Mowed lawn, bare ground, pavement or gravel, chunky bark used for mulch
- No highly flammable shrubs over 3 feet tall
- No vines or small trees underneath larger trees
- Trees within 30 feet of your house should not touch each other or touch the house
- A clear view of your home from the street
- Easy to see through areas of forest or brush within ½ mile of your home

Figure 1. Fire risk descriptions used in the survey.

configurations of vegetation lead to high, medium and low fire risk landscapes (Figure 1). This question is immediately followed by asking respondents to compare these descriptions to the vegetation around their house and neighbourhood, and whether they perceive the risk of their house being damaged by a wildfire as high, medium or low.

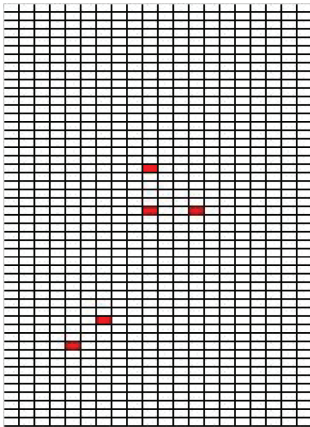
Since the choice questions require the respondent to consider trade-offs between the cost of fuel reduction treatments and the risk of wildfire damage to homes, it was important to make sure respondents had a basic understanding of risk concepts. Thus, to assist survey participants in developing an intuitive understanding of risk concepts used in the choice scenarios, wildfire risk was characterized using a spatial ‘chance grid’. This grid illustrates the probability of a home being damaged by a wildfire (Figure 2) and a risk ladder (Figure 3), positioning wildfire risk relative to other ordinary risk factors (such as dying in a road accident).

Both of these risk communication devices have been used in past surveys as a way of conveying to respondents relative and absolute risks (González-Cabán and Sánchez 2017; Holmes et al. 2013; Krupnick et al. 2002; Loomis and duVair 1993; Smith and Desvousges 1987).

Prior to asking the choice questions, homeowners were asked what individual wildfire prevention activities, if any, they have undertaken in the past or intend to undertake in the future to mitigate wildfire risk. At the end of the survey, we also collected information on individual characteristics, including educational attainment, gender, household income, race/ethnicity and respondents’ age.

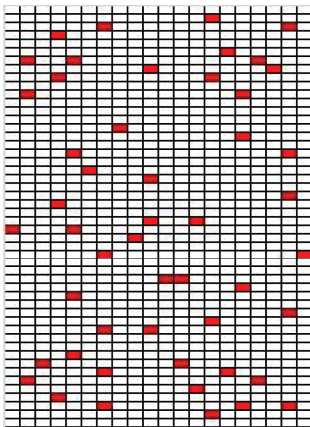
CHANCE GRIDS

(1) UPPER CHANCE GRID: Annual chance



Another way to illustrate the Average Annual Chance of a wildfire damaging your house is shown in the diagram to the left. The “chance grid” shows a neighborhood with 1000 houses, and each square represents one house. The white squares are houses that have not been damaged or destroyed by wildfire, and the red squares are houses that have been damaged or destroyed. Consider this to be a typical, or average, occurrence each year for this neighborhood. To get a feeling for this chance level, close your eyes and place the tip of a pen inside the grid. If it touches a red square, this would signify your house was damaged or destroyed by wildfire.

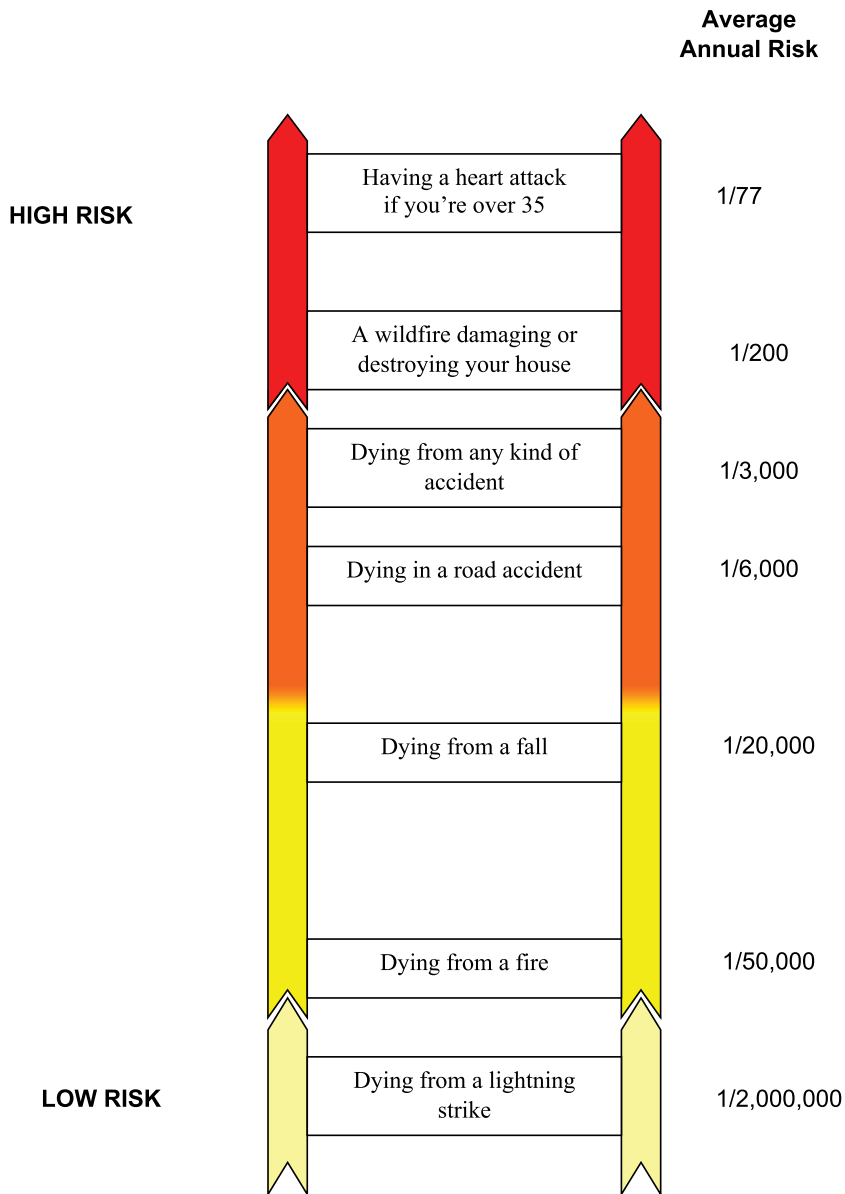
(2) LOWER CHANCE GRID: Ten year chance



The chance that your house will be damaged by wildfire during a **ten year period** is approximately 10 times the chance that it would be damaged or destroyed in a single year. The Average Ten Year Chance is shown for the same neighborhood over a ten year period, where red squares represent houses that have been damaged or destroyed during a ten year period and white squares are houses that have not been damaged or destroyed.

Figure 2. Risk grids to convey the relevant degree of wildfire risk to homeowner survey participants (Holmes et al. 2013).

The core of the choice experiment survey uses three attributes to construct choice alternatives: (1) *risk (%)* of the respondents house being damaged by wildfires in the next 10 years (this variable varied over five levels, from 1% to 5%, where 5% was the baseline risk and respondents were told this per cent was associated with no new investments in wildfire protection programmes);⁵ (2) monetary damage (*loss*) to respondents’ property from a wildfire (dollar amounts varied over 10 levels that ranged from \$10,000 to \$100,000, where \$100,000 was the baseline loss and respondents were told this was the monetary amount of damage associated with no new investments in wildfire protection programmes) and (3) one-time *cost* to the household for the ten-year programme (the *cost* of the programmes varied over 10 levels ranging from \$25 to \$1500 for the public programme and 9 levels from \$50 to \$1500 for the private programme) with zero cost associated with the ‘Do Nothing Additional’ or status quo alternative. To assist respondents in thinking about trade-offs between programme costs and expected losses, information on the *expected ten-year loss* = *risk* $\times$ *loss* was included in the choice set, although this variable was not included as a separate variable in the econometric models due to its redundancy with the risk and loss variables.



This “risk ladder” shows the risk of everyday hazards occurring to you over the next 12 months. If you are over 35 years old, the highest risk shown on the ladder is of having a heart attack (this will happen to approximately 1 in 77 people). The risk of your house being damaged by a wildfire if you live in or near a heavily wooded area (this will happen to approximately 1 in 200 homeowners) is quite a bit larger than the risk of dying from a fire (this will happen to approximately 1 in 50,000 people).

Figure 3. Risk ladder used to illustrate to survey participants the risk of wildfires relative to other, ordinary events (Holmes et al. 2013).

The risk, damage and cost variables were organized into three alternatives: a *public programme* that was described in the survey as involving fuel reduction in the forest and undeveloped areas of the respondents' neighbourhood using prescribed burning, mechanical fuel reduction and herbicide treatments; a *private programme*, involving removal or trimming of vegetation around the respondents' home and the status quo 'do nothing additional'. No mention in the survey was made of whether performing additional vegetation management around the home would affect a homeowner's insurance premiums. In part, this was due to the wide variety of different insurance companies that different homeowners likely had and those companies associated guidelines for determining household premiums. This omission is common to both the online and mail surveys, so it is unlikely to affect the *relative* comparison of mail and online survey results with respect to attribute non-attendance and WTP.

The public programme lump sum cost to homeowners, which in the survey indicated it would go into a County Trust Fund to be used only for the Ten-year Vegetation Management Programme, and a citizen advisory board would review the expenditure from the fund annually. However, there was no explicit mention of the implementation rule, such as 'the alternative selection by the majority of respondents would be implemented'. This shortcoming should be rectified in future applications. However, since this same limitation was in both mail and online surveys, it should not affect the *relative* comparison of the two survey modes on attribute non-attendance or WTP. Table 1 lists the attributes and levels. The combination of levels of risk, damage and cost in each choice set was based upon an efficient fractional factorial design using Ngene software (Rose et al. 2014). The selected D-optimal experimental design has 15 blocks, each having 3 choice sets. Note that the 'do nothing additional' alternative establishes a baseline having zero cost, with homes facing 5% *risk* and \$100,000 property damage (*loss*). Table 2 presents an example of one of the three choice sets presented in the survey.

Table 1. Attribute and Levels.

Attribute	Levels
Chance of your house being damaged in the next 10 years (<i>risk</i>)	1, 2, 3, 4 and 5%
Damage to property (<i>loss</i>)	\$10,000, \$20,000, \$30,000, \$40,000, \$50,000, \$60,000, \$70,000, \$80,000, \$90,000 and \$100,000
One-time cost to you for the 10-year <i>public</i> programme	\$25, \$50, \$100, \$200, \$400, \$600, \$800, \$1000, \$1300 and \$1500
One-time cost to you for the 10-year <i>private</i> programme	\$50, \$100, \$200, \$400, \$600, \$800, \$1000, \$1300 and \$1500

Table 2. Example of the choice set.

	Alternative 1	Alternative 2	Alternative 3
	Public Fire Prevention	Private Fire Prevention	Do nothing additional
Chance of your house being damaged in the next 10 years	30 in 1000 (3%)	20 in 1000 (2%)	50 in 1000 (5%)
Damage to property	\$20,000	\$40,000	\$100,000
Expected 10-year loss = Chance x damage	\$600 during 10 years	\$800 during 10 years	\$5000 during 10 years
One-time cost to you for the ten-year programme	\$800	\$1000	\$0
I would choose:	☐	☐	☐
Please check one box			

3.1. Sample design

A stratified sample of Colorado households was collected in 2016–2017 and was primarily focused on obtaining responses from households living in areas considered to be at meaningful risk of

wildfires using wildfire risk maps provided by the state of Colorado (Figure 4; Colorado State Forest Service 2018). In both survey modes, participants were recruited in the same format using a random digit dialling of households to identify willing homeowners, followed by a random assignment of survey participants to mail or online surveys. Survey participants received the same survey design (e.g. same questions and choice sets). Following Dillman, Smyth, and Christian (2014), four follow-up contacts were made for non-responding homeowners. The relative sampling rates were as follows: one homeowner randomly selected from the low wildfire risk zone, two homeowners were randomly drawn from a moderate wildfire risk zone and three homeowners were randomly drawn from zones rated as having high and highest wildfire risk.

4. Econometric model of choice experiment responses

Choice experiments are used to model individual's choices among two or more alternatives, consisting of varying levels of policy-relevant attributes, thus allowing researchers to estimate economic values of various attributes and attribute bundles (Holmes, Adamowicz, and Carlsson 2017; Train 2009). CE analysis is generally based upon the random utility maximization theory, assuming that individuals select a good that provides the greatest utility among those available to them (Champ, Boyle, and Brown 2017). The utility model is considered to be the sum of systematic (V_{nj}) and random (ε_{nj}) components:

$$U_{nj} = V_{nj} + \varepsilon_{nj} \equiv \sum_{k=1}^K \beta_{nk} x_{nj,k} + \varepsilon_{nj} \quad (1)$$

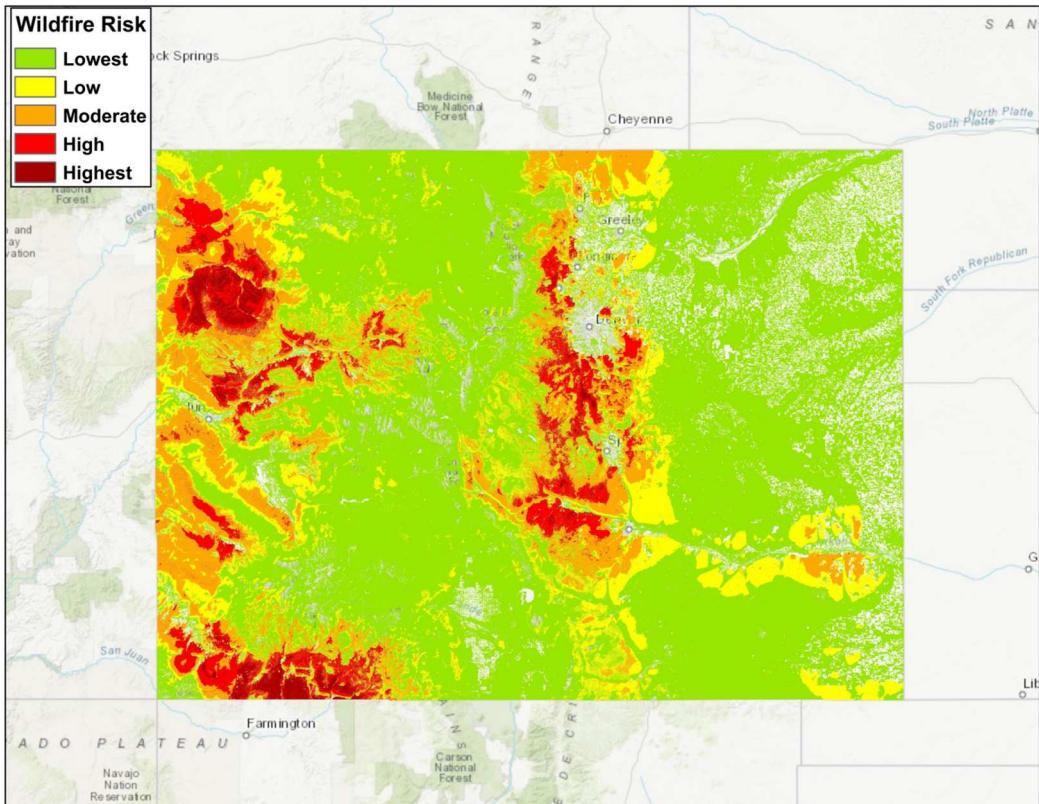


Figure 4. Colorado wildfire risk map (data source: Colorado State Forest Service 2018).

where x_{nj} is a vector of K explanatory variables observed by the analyst for alternative j and respondent n , β_{nk} is a vector of preference parameters and ε_{nj} is an error term that reflects factors unobservable to the researcher and hence is treated as a stochastic variable.

To estimate the model in Equation (1), assumptions are made about the specification of the utility function and distribution of the error terms. The standard MNL is based on the idea that when faced with more than one alternative in a given choice set, respondents choose the alternative that maximizes their utility. In the MNL model, the unobserved stochastic variable is assumed to be independently and identically distributed (IID) following a type I extreme value distribution. The probability of individual n choosing alternative j from the set Θ is

$$P_n(j) = \frac{\exp(\mu\beta x_{nj})}{\sum_{j \in \Theta} \exp(\mu\beta x_{nj})} \quad (2)$$

where μ is a scale parameter that is typically set equal to one.⁶

While the MNL model assumes that preference parameters are constant across the population of interest, more advanced approaches relax this assumption. Parameter heterogeneity can be represented by an RPL model, which assumes that preferences are continuously distributed across individuals, and requires that the researcher specify the nature of the distribution (Hensher, Rose, and Greene 2015). The independence of irrelevant alternatives assumption, which is imposed in the MNL model, is relaxed by introducing additional stochastic components to the utility function through β_n . These components allow the preference parameters for the x_{jn} explanatory variables to directly incorporate heterogeneity:

$$\beta_{nk} = \beta_k + \Gamma v_{nk} \quad (3)$$

where β_k is the mean value for the k th preference parameter, v_{nk} is a random variable with zero mean and variance equal to one and Γ is the main diagonal of the lower triangular matrix that provides an estimate of the standard deviation of the preference parameters across the sample. This is true only when the marginal utilities are assumed to be normally distributed across respondents, and the correlation of preferences across attributes is permitted.

Probabilities in the RPL model are weighted averages of the standard logit formula evaluated at different values of β . The weights are determined by the density function $f(\beta|\theta)$, where θ is a parameter vector describing the distribution of $f(\bullet)$. Let π_{nj} be the probability that an individual n chooses alternative j from set J , such that

$$\pi_{nj} = \int L_{nj}(BX_j) f(\beta|\theta) d\beta \quad (4)$$

where

$$L_{nj}(BX_j) = \frac{\exp(\mu\beta X_j)}{\sum_{j=1}^J \exp(\mu\beta X_j)} \quad (5)$$

The function $f(\beta|\theta)$ can be simulated using random draws from various functional forms (Train 2009). We use Halton 2500 draws from the normal and triangular distributions to estimate Γ for the random parameters in the RPL model. The RPL model captures heterogeneity via a continuous probability distribution for preference parameters.⁷

The ECLC model with AN-A was developed by Scarpa et al. (2009) to incorporate AN-A behaviour into the estimation. The ECLC method classifies respondents into latent classes based on their AN-A behaviour. Each latent class in the ECLC model represents a different pattern of attribute attendance. For the attribute coefficients that are not considered in the class (non-attended attributes), a zero-utility weight is assigned, essentially constraining those specific coefficients to zero and all other coefficients that are estimated (attended attributes) are constrained to be equal across classes.

The ECLC model is based on the conditional probability of belonging to a given group (or class) c , and the probability of observing a set of T choices, $y_n = \{y_1, y_2, \dots, y_T | \beta_c\}$ by individual n is the product of logits (Scarpa et al. 2009):

$$P_n(y_n | \beta_c) = P_t(i_1, \dots, i_T | \beta_c) = \prod_{t=1}^T \frac{\exp(X_{it}\beta_c)}{\sum_k \exp(X_{kt}\beta_c)} \quad (6)$$

Using the law of total probability, the unconditional probability of the panel of choices of individual n is obtained by summing the conditional probabilities over the finite set of c logit membership probabilities of the various attribute attendance groups and scale group. Therefore, we get the following:

$$P_n(y_n) = \sum_c P(c) P_n(i_t | \beta_c) = \sum_c \frac{\exp(\alpha_c)}{\sum_c \exp(\alpha_c)} \prod_{t=1}^T \frac{\exp(X_{it}\beta_c)}{\sum_k \exp(X_{kt}\beta_c)} \quad (7)$$

where α denotes group-specific constants identified by ensuring they sum to zero. See Scarpa et al. (2009) for more information on the modelling strategy for the ECLC approach.

The final model used in the study is LCRPL AN-A, developed by Hess et al. (2013), which combines the random parameter logit model with the latent class model and accounts for AN-A. The LCRPL AN-A model allows some of the random heterogeneity to be captured in the randomly distributed non-zero elements within the β coefficients. For this model, each element in β follows a distribution in the sample, which means that for any given class in the LCRPL AN-A model, the coefficients not fixed to 0 allow for additional random heterogeneity. Following Hess et al. (2013), the likelihood function for individual n is written as follows:

$$L(y_n | \Omega, \pi) = \sum_{c=1}^C \pi_c \int \prod_{\beta} \prod_{t=1}^T P(i_{nt}^* | \beta_c = \beta \circ \Lambda_c) f(\beta | \Omega) d\beta \quad (8)$$

where i_{nt}^* is the alternative selected by individual n in choice task t . The vector β and π (vector of probabilities for the C classes) need to be estimated. The probability for class c is $0 \leq \pi_c \leq 1$ and $\sum_{c=1}^C \pi_c = 1$. The class probability specification is

$$\pi_c = \prod_{k=1}^K (\Lambda_{c,k} P_{k,1} + (1 - \Lambda_{c,k}) P_{k,2}) \quad (9)$$

where $P_{k,1} = \frac{1}{e^{\delta_k} + 1}$ and $P_{k,2} = \frac{e^{\delta_k}}{e^{\delta_k} + 1}$. The $\Lambda_{c,k}$ gives the entry in Λ relating to attribute k in class c . The multivariate distribution for all elements in β with a vector of parameters Ω is given by $f(\beta | \Omega)$. See Hess et al. (2013) for more detailed information on the LCRPL AN-A model.

In a CE, the marginal WTP estimates of the attributes are used to construct total WTP for policy-relevant scenarios. Valuation of attributes is accomplished by dividing non-cost attribute coefficients by the absolute value of the cost coefficient (Holmes, Adamowicz, and Carlsson 2017). The marginal WTP estimates of the attributes are as follows:

$$WTP = \frac{\beta_{attribute}}{|\beta_{Cost}|} \quad (10)$$

The WTP estimate can be interpreted as the amount of money an individual is willing to forego for a one-unit reduction in risk or damage (i.e. a marginal change in the attribute). If the attribute is a binary variable, indicating whether or not an attribute is present, then it is not possible to speak of a marginal change. For this scenario, the ratio shown in Equation (10) represents the amount of money a respondent is willing to pay to make an attribute available that would otherwise be

unavailable. In our case, the numerator in Equation (10) is the alternative-specific constants representing the availability of a public or private wildfire mitigation programme.

For this study, we contrast results from the MNL, RPL and LCRPL AN-A models with the ECLC AN-A model (Scarpa et al. 2009) to ascertain if AN-A behaviour has an impact on the WTP estimates. For the ECLC AN-A model, we used the 2^k combination of attributes, classifying respondents into 8 groups⁸: all attributes attended, cost non-attended, loss non-attended, risk non-attended, both cost and loss non-attended, cost and risk non-attended, loss and risk non-attended and cost, loss and risk non-attended.⁹

5. Results

5.1. Comparison of descriptive statistics between survey modes

We obtained 528 complete surveys out of 1614 (1000 online and 614 mail); 323 online and 205 mail surveys, with response rates of 32% and 33%, respectively. Approximately the same proportion of respondents from both survey methods reported prior experiences with wildfire (online 43.3% and mail 42.9%), and no statistical differences were found for conducting activities to reduce wildfire risk around home and property (Table 3). However, significant differences were found across survey modes for variables describing age, income, per cent having a college degree and having travel plans changed because of a wildfire. In particular, online survey participants were younger (56 vs 64), had higher incomes (\$79,000 vs \$58,500) and a higher percentage of households had at least a bachelor's degree (67% vs 44%). After reading the descriptions of high-, medium- and low-fire-risk landscapes around homes and neighbourhoods, respondents were asked whether they perceived their house and neighbourhood to be at high, medium and low risk. About one in ten households perceived they were living in a high-risk area for both survey modes.

A homogeneity test for the two survey mode datasets was done to determine if respondents come from the same population (H_0 = sample distributions are the same for both datasets), to determine if data should be pooled or separated by survey mode. Results show that we reject the null hypothesis (alpha level <0.01), providing evidence supporting the assumption that the sample distributions are not the same, and the sample data come from different populations. This suggests separate analysis should be done for each survey mode.

Table 3. Variable descriptive statistics by the survey mode.

Variable	Description	Mail Survey Mean (std. dev.)	Online Survey Mean (std. dev.)
Health*** (dummy variable)	Health of respondent or family member suffered from breathing smoke from wildfire; if Yes = 1; else = 0	0.09 (0.28)	0 (0.00)
Travel** (dummy variable)	Household travel plans changed because of a wildfire; if Yes = 1; else = 0	0.33 (0.47)	0.43 (0.50)
Personal experience (dummy variable)	If either (health = 1 or travel = 1) = 1; else = 0	0.43 (0.50)	0.43 (0.50)
Firewise (dummy variable)	Household conducted at least one activity to reduce wildfire risk; if Yes = 1; else = 0	0.83 (0.38)	0.77 (0.42)
High risk (dummy variable)	Respondent indicated that home is located in a high fire risk neighbourhood; if Yes = 1; else = 0	0.08 (0.28)	0.08 (0.27)
Age***	Respondent's age	63.7 (11.92)	55.8 (12.6)
Gender (dummy variable)	Female respondent; if Yes= 1; else = 0	0.43 (0.50)	0.43 (0.49)
Income***	Household annual income	\$58,548 (43,214)	\$78,986 (37,708)
Education***	Completed at least a bachelor's degree	0.44 (0.50)	0.67 (0.47)

Note: *** indicates the mean values are statistically significantly different between survey modes at alpha level <.01. ** indicates mean values are statistically significantly different between survey modes at alpha level <.05.

5.2. Econometric results

Data analysis was conducted using NLogit 6 software (Econometric Software, Inc. 2016). Exploring the choices made by survey participants, we find that 82% (83%) of mail (online) survey respondents select the public programme when cost is less than half the expected damage and 58% (53%) select the private programme. This suggests that the pattern between survey modes is consistent. However, survey participants for both survey modes appear to be more circumspect when selecting public over private programmes.

Tables 4–6 present the econometric results for the two survey modes. For the MNL model results (Tables 4 and 5), both survey modes find the *cost* coefficient to be negative and statistically significant, indicating that respondents took the dollar amount they were asked to pay seriously. In economic terms, the statistically significant negative sign is consistent with an inverse relationship between price and probability of selecting a programme, implying internal validity of the results.

Table 4. Multinomial logit (MNL), Random parameter logit (RPL), and Equality Constrained Latent Class Attribute Non-Attendance (ECLC AN-A) models: estimates of preference parameters estimated using **mail** survey mode for wildfire hazard mitigation programmes (The dependent variable is the alternative selected in the choice questions).

Variable	MNL	RPL	Std Dev	ECLC AN-A
<i>risk</i> (%)	−0.0250 (0.0507)	0.0128 (0.0834)	0.4538*** (0.1307)	−5.4637*** (1.0131)
<i>loss</i> (\$1000)	−0.0053** (0.0025)	0.0039 (0.0055)	0.0437*** (0.0073)	−0.1155*** (0.0347)
<i>cost</i> (\$)	−0.0009*** (0.0002)	−0.0018*** (0.0003)	0.0018*** (0.0003)	−0.0321*** (0.0048)
<i>public programme</i>	−0.2967 (0.2750)	0.3261 (0.4058)		0.4180 (0.3147)
<i>private programme</i>	−0.0037 (0.2679)	0.8480** (0.3999)		1.0443*** (0.3074)
<i>travel*public</i>	0.2669 (0.2266)	0.5200 (0.4012)		0.7762** (0.3529)
<i>travel*private</i>	−0.3286 (0.2424)	−0.3712 (0.4202)		−0.2488 (0.3343)
<i>bachelors*public</i>	0.5492** (0.2157)	0.8686** (0.3845)		0.4784 (0.3331)
<i>bachelors*private</i>	−0.0419 (0.2196)	0.1378 (0.3903)		−.2916 (0.3190)
<i>retire*public</i>	−.9747*** (0.2308)	−1.2726*** (0.4009)		−1.0578*** (0.3732)
<i>retire*private</i>	−0.4934*** (0.2203)	−0.8179** (0.3922)		−0.4370 (0.3242)
<i>n</i> ^a	603	603		603
McFadden pseudo-R ²	0.0574	0.1903		0.2353
Log Likelihood	−548.86	−491.01		−463.74
AIC	1119.7	1008.0		963.5
BIC	1167.2	1064.1		1041.1
Halton Draws	—	2500		—
Class Shares				% of Class
Total Attendance				15.0**
Cost Non-Attendance				0.0
Loss Non-Attendance				0.0
Risk Non-Attendance				0.0
Cost & Loss Non-Attendance				0.96
Cost & Risk Non-Attendance				5.3*
Loss & Risk Non-Attendance				37.5***
Cost, Loss, & Risk Non-Attendance				41.2***

Note: standard errors in parentheses.

***Indicates significance at the 0.01 alpha level.

**Indicates significance at the 0.05 alpha level.

*Indicates significance at the 0.10 alpha level.

^aThere are 201 usable surveys; however, each respondent had 3 choice sets presented to them. Therefore, there is a total of 603 observations in the econometric models.

Table 5. Multinomial logit (MNL), Random parameter logit (RPL), and Equality Constrained Latent Class Attribute Non-Attendance (ECLC AN-A) models: estimates of preference parameters estimated using **online** survey mode for wildfire hazard mitigation programmes (The dependent variable is the alternative selected in the choice questions).

Variable	MNL	RPL	Std Dev	ECLC AN-A
<i>risk</i> (%)	−0.1686*** (0.0365)	−0.1974*** (0.0601)	0.5375*** (0.0851)	−10.6398*** (1.2360)
<i>loss</i> (\$1000)	−0.0077*** (0.0018)	−0.0104*** (0.0032)	0.0332*** (0.0041)	−0.4239*** (0.0420)
<i>cost</i> (\$)	−0.0011*** (0.0001)	−0.0017*** (0.0002)	0.0017*** (0.0002)	−0.0493*** (0.0045)
<i>public</i> programme	−0.0665 (0.2170)	0.3292 (0.3202)		0.9661*** (0.2468)
<i>private</i> programme	−0.0167 (0.2228)	0.3672 (0.3292)		0.9518*** (0.2622)
<i>travel</i> * <i>public</i>	0.3837** (0.1765)	0.6378** (0.3048)		0.3315 (0.3139)
<i>travel</i> * <i>private</i>	0.2431 (0.1844)	0.5319* (0.3135)		0.1792 (0.3190)
<i>bachelors</i> * <i>public</i>	0.7085*** (0.1812)	1.0895*** (0.3098)		0.6284** (0.2988)
<i>bachelors</i> * <i>private</i>	0.4207** (0.1855)	0.6504** (0.3134)		0.3620 (0.3010)
<i>retire</i> * <i>public</i>	−0.8305*** (0.2263)	−1.1065*** (0.3980)		−0.8802** (0.3624)
<i>retire</i> * <i>private</i>	−0.5533** (0.2305)	−0.7471* (0.3996)		−0.3862 (0.3652)
<i>n</i> ^a	966	966		966
McFadden pseudo-R ²	0.0829	0.1894		0.2463
Log Likelihood	−929.28	−846.01		−786.61
AIC	1880.6	1718.0		1609.2
BIC	1934.0	1781.1		1696.6
Halton Draws	—	2500		—
Class Shares				% of Class
Total Attendance				25.8***
Cost Non-Attendance				1.7
Loss Non-Attendance				0.0
Risk Non-Attendance				0.0
Cost & Loss Non-Attendance				2.8
Cost & Risk Non-Attendance				3.7*
Loss & Risk Non-Attendance				17.7***
Cost, Loss, & Risk Non-Attendance				48.3***

Note: standard errors in parentheses.

***Indicates significance at the 0.01 alpha level.

**Indicates significance at the 0.05 alpha level.

*Indicates significance at the 0.10 alpha level.

^aThere are 322 usable surveys; however, each respondent had 3 choice sets presented to them. Therefore, there is a total of 966 observations in the econometric models.

There are also other similarities between the mail and online survey results. Although the anticipated negative signs on *risk* and *loss* are found in both survey modes, and the coefficient estimate on *loss* is statistically significant in both samples, the estimated coefficient on *risk* is only statistically significant in the online sample. Similarly, the *public* and *private* programme alternative-specific constants (ASCs) are not statistically significant and are negative for both survey mode samples; respondents prefer the status quo to the alternative programmes. Three sociodemographic variables were included in the model by interacting with programme type to capture heterogeneity; *bachelors* dummy variable indicating if respondents have at least a bachelors degree, *retire* dummy variable indicating if respondents are older than 67 years of age and a *travel* dummy variable indicating if respondents' travel plans were changed due to a wildfire. For the online survey mode, those with at least a bachelor's degree indicated support for both public and private programmes. However, those respondents of retired age did not support any of the programmes. Similar results were

Table 6. Latent class random parameter logit attribute non-attendance (LC RPL AN-A) model estimates of homeowner preference parameters for wildfire hazard mitigation programmes for **mail** and **online** survey respondents

Variable	Mail Survey		Online Survey	
	Coefficient	Std. Dev.	Coefficient	Std. Dev.
<i>risk</i> (%)	−0.0250 (2.2196)	0.0250 (2.2196)	−0.1686 (0.2469)	0.1686 (0.2469)
<i>loss</i> (\$1000)	−0.0053 (0.0208)	0.0053 (0.0208)	−0.0077 (0.0106)	0.0077 (0.0106)
<i>cost</i> (\$)	−0.0009 (0.0011)	0.0009 (0.0011)	−0.0011* (0.0006)	0.0011* (0.0006)
<i>public programme</i>	−0.2967 (0.3266)		−0.0665 (0.2256)	
<i>private programme</i>	−0.0037 (0.3042)		−0.0167 (0.2381)	
<i>travel*public</i>	0.2669 (0.1978)		0.3837*** (0.1283)	
<i>travel*private</i>	−0.3286* (0.1784)		0.2431* (0.1404)	
<i>bachelors*public</i>	0.5492*** (0.1728)		0.7085*** (0.1387)	
<i>bachelors*private</i>	−0.0419 (0.1659)		0.4207*** (0.1421)	
<i>retire*public</i>	−0.9747*** (0.1956)		−0.8305*** (0.1677)	
<i>retire*private</i>	−0.4934*** (0.1769)		−0.5533*** (0.1798)	
Class Shares	% of Class		% of Class	
Total Attendance	13.0		12.9	
Cost Non-Attendance	13.0		12.9	
Loss Non-Attendance	13.0		12.9	
Risk Non-Attendance	12.6		10.9	
Cost & Loss Non-Attendance	12.9		12.9	
Cost & Risk Non-Attendance	13.0		12.9	
Loss & Risk Non-Attendance	9.7		12.0	
Cost, Loss, & Risk Non-Attendance	13.0		12.9	
n	603 ^a		966 ^b	
McFadden pseudo-R ²	0.10		0.12	
Log Likelihood/AIC/BIC	−543.31/ 1122.6 / 1200.3		−916.76/1869.5/1956.9	

Note: standard errors in parentheses.

*Indicates significance at the 0.10 alpha level.

**Indicates significance at the 0.05 alpha level.

***Indicates significance at the 0.01 alpha level.

^aThere are 201 usable surveys; however, each respondent had 3 choice sets presented to them. Therefore, there is a total of 603 observations in the econometric models.

^bThere are 322 usable surveys; however, each respondent had 3 choice sets presented to them. Therefore, there is a total of 966 observations in the econometric models.

found with mail survey participants, except for those respondents with a bachelor's degree for the private programme, in which they were indifferent between supporting the programme and the status quo.

5.3. Exploring random parameter logit in mail vs online survey results

The RPL model results in Tables 4 and 5 for mail and online surveys, respectively, show that the parameter estimates and derived standard deviations for random parameters *risk* and *loss* (normally distributed) and the *cost* (one-sided or constraint triangular distributed) are statistically significant, suggesting the existence of preference heterogeneity. However, the mean coefficients for *risk*, *loss* and *cost* in the online sample are statistically significant, but only *cost* is high in the mail sample. The interaction of the retirement age variable with the public programme variable suggests that older respondents (those of retirement age) do not support fuel mitigation programmes for their

community; rather, they prefer the status quo in both survey modes. This is similar to the online survey results for the private programme, but not for the mail sample where older respondents have a small preference (0.0301) for a fuel mitigation programme for their property. Respondents in the online sample with at least a bachelor's degree and travel plans changed due to wildfires prefer both fuel mitigation programmes for their property and community relative to the status quo. Overall, mail survey respondents support a *private* programme, but those respondents with at least a bachelor's degree also support a *public* programme.

5.4. Exploring attribute non-attendance in mail vs online survey results

In order to test the hypothesis that differences in the magnitude and statistical significance of coefficients in mail versus online surveys, as well as associated WTP values, could be explained by the inferred presence of AN-A behaviour, we used the ECLC method (Scarpa et al. 2009). Tables 4 and 5 show that in both survey modes, the ECLC AN-A models outperform both the MNL and RPL models, based on the model fit criteria (AIC, BIC, log-likelihood, McFadden's pseudo R^2). This suggests that AN-A behaviour is displayed by respondents in both mail and online survey modes. The *risk*, *loss* and *cost* parameter estimates in the AN-A model have the correct sign and are highly significant. While the *private* programme ASC is statistically significant for the mail sample, both the *private* and *public* programme ASCs are statistically significant in the online sample. Retired-age respondents have a weak preference for the public programme in the online survey, while highly educated respondents prefer a public programme over status quo in the online survey mode.

Comparing parameter estimates, the ECLC AN-A model results show that the *risk*, *loss* and *cost* coefficients are large for online relative to the mail sample. In addition, the parameter estimates for *public* and *private* fuel reduction programmes become statistically significant when we account for AN-A in the online survey.

Focusing on the results shown in the bottom section of Tables 4 and 5, in the ECLC AN-A model, the mail survey results suggest that *cost* is never ignored in isolation, but always in combination with *loss* (0.96% of choices), *risk* (5.3% of choices) and with both *loss* and *risk* (in 41.2% of choices).¹⁰ Similar results hold for the online survey, where 1.7% ignore *cost* in isolation, 2.8% ignore in combination with *loss*, 3.7% in combination with *risk* and 48.3% in combination with both *loss* and *risk*. Overall, *cost* is ignored in 56.5% of choices by online respondents and about 47.5% for mail respondents.¹¹ As the parameter estimates on the *cost* attribute are an essential component of WTP estimates, it can be anticipated that controlling for non-attendance can have a substantial impact on estimates of economic values. Generally, these results suggest that both samples used simplifying heuristics in making choices among alternatives (the mail sample estimates indicated 15% **total** attendance, while the online sample indicated about 26% **total** attendance), indicating that respondents typically focus on a select subset of attributes when making decisions.

5.5. Exploring latent class random parameter attribute non-attendance logit in mail vs online survey results

Table 6 presents the results of the LCRPL AN-A model; the random variables are *risk*, *loss* and *cost*. The *cost* random variable is one-sided triangularly distributed, and the *risk* and *loss* random variables are normally distributed.¹² All three standard deviation estimates in the mail survey are non-significant, suggesting there is no unobserved preference heterogeneity. Similar results are found for the online sample; however, the *cost* mean coefficient and standard deviation are statistically significant. The interaction of retirement age variables with programmes suggests that older respondents do not support either of the fuel mitigation programmes, they prefer the status quo in both survey modes. Respondents in the online sample with at least a bachelor's degree and travel plans changed due to wildfires prefer both fuel mitigation programmes relative to the status quo. However, in the

mail survey, respondents with at least a bachelor's degree only prefer the public programme. An interesting result is that those respondents who changed their travel plans prefer the status quo over the private programme in the mail survey.

About 13% of mail respondents did not attend to *cost*, *loss* and *risk* in their choice decision-making when these attributes are considered singly. A similar percentage is found for online respondents, except for *risk*, which is slightly lower at 11%. However, when considering the pairwise non-attendance for *cost* (in combination with *loss* and *risk*), total non-attendance for this attribute is 51.9% (13%+12.9%+13%+13%) for mail and 51.6% (12.9%+12.9%+12.9%+12.9%) for online respondents.

5.6. Willingness to pay in mail vs online survey results

The mean WTP for all models were estimated using Equation (10). Table 7 compares WTP across the four econometric models and two survey modes. The results indicate that WTP estimates for *public* and *private* programmes are negative (indicating a preference for the status quo over either programme) for those respondents who are of retirement age in both the mail and online survey modes. Respondents with at least a bachelor's degree have positive WTP values indicating they prefer wildfire risk mitigation programmes over the status quo, although more frequently in the online survey mode than in mail.

The absolute value of the welfare losses and gains for the interacted *private* and *public* programmes are the largest with the MNL, RPL and the LC RPL ANA-A. In the ECLC AN-A model, the WTP value estimates for *public* and *private* programmes are substantially lower, and several welfare estimates are not significantly different from zero in both survey modes. This suggests that when AN-A is explicitly modelled, the resulting welfare estimates are more conservative. By accounting for respondents who likely ignored certain attributes, the ECLC model avoids the upward bias in WTP often found in models that assume full attribute attendance.

Mode-specific interpretations further reveal that there are more significant WTP values in the online than in the mail survey. Statistical differences in WTP estimates between MNL, RPL, ECLC AN-A and LCRPL AN-A models and across survey modes were tested for only the significant WTP estimates using the complete combinatorial method (Poe, Giraud, and Loomis 2005). When comparing WTP estimates across survey modes, statistical differences (alpha level 0.01) are found for the *loss* WTP estimate in the ECLC AN-A model and travel plans change interacted with private programme in the LCRPL AN-A model. Comparing WTP estimates between models within survey mode, a total of 10 (4 mail and 6 online) statistical differences were found. Within the mail survey, statistically significant differences were found for *retire*public* WTP estimates in the ECLC AN-A model compared to MNL, RPL and LCRPL AN-A models, at alpha level 0.01. *Private* programme WTP are statistically significantly different when comparing RPL with the ECLC AN-A model. For the online survey, statistical differences are found for *retire*public* interaction WTP in the ECLC AN-A model compared to MNL and RPL. We also found statistical differences for *bachelor*public* interaction WTP in the ECLC AN-A with the other 3 models. Lastly, the *risk* WTP in ECLC AN-A is statistically different (alpha level 0.10) from the MNL model.

6. Discussion and conclusions

This paper evaluated the convergent validity of mail versus online survey modes for stated preference choice experiments using identical surveys in the context of programmes for reducing wildfire risk. Results show that both survey modes have similar response rates, around 30%. While there were significant differences in three of four demographic characteristics of respondents (age, income and education levels) between survey modes, there were no significant differences between survey modes in respondents' fire risk perception and prior fire experience.

Table 7. One-time WTP for Public and Private Wildfire Risk Reduction Actions for the Multinomial Logit (MNL), Random Parameter Logit (RPL), Equality Constrained Latent Class Attribute Non-Attendance (ECLC AN-A), and Latent Class Random Parameter Logit Attribute Non-Attendance (LC RPLAN-A) models by the Survey Mode.

Attribute/Programme Type	Mail	Online
<i>MNL Model^a</i>	<i>Mean WTP^b</i>	<i>Mean WTP^b</i>
Risk	–	–\$154 (–230, –78)
Loss	–\$6.0 (–12, .22)	–\$7.0 (–10, –3)
Public Programme	–	–
Private Programme	–	–
Travel*Public	–	–\$15 (–418, 388)
Travel*Private	–	–
Bachelors*Public	\$618 (73, 1163)	\$647 (297, 998)
Bachelors*Private	–	\$384 (35, 733)
Retire*Public	–\$1,097 (–1759, –435)	–\$758 (–1186, –331)
Retire*Private	–\$555 (–1101, –9)	–\$505 (–933, –78)
<i>RPL Model</i>		
Risk	\$10 (–9, 28)	–\$116 (–137, –96)
Loss	\$2.2 (–0.35, 5)	–\$6.3 (–8, –5)
Public Programme	–	–
Private Programme	\$642 (615, 670)	–
Travel*Public	–	\$504 (480, 526)
Travel*Private	–	\$420 (400, 439)
Bachelors*Public	\$658 (630, 687)	\$860 (821, 900)
Bachelors*Private	–	\$493 (477, 509)
Retire*Public	–\$964 (–1006, –922)	–\$874 (–914, –834)
Retire*Private	–\$620 (–647, –593)	–\$589 (–617, –563)
<i>ECLC AN-A</i>		
Risk	–\$170 (–202, –139)	–\$216 (–240, –191)
Loss	–\$3.6 (–5, –2)	–\$8.5 (–9, –8.1)
Public Programme	–	\$20 (9, 30)
Private Programme	\$33 (14, 51)	\$19 (8, 30)
Travel*Public	24 (1, 47)	–
Travel*Private	–	–
Bachelors*Public	–	\$13 (0.8, 25)
Bachelors*Private	–	–
Retire*Public	–\$33 (–57, –9)	–\$18 (–33, –3)
Retire*Private	–	–
<i>LC RPL AN-A</i>		
Risk	–	–
Loss	–	–
Public Programme	–	–
Private Programme	–	–

(Continued)

Table 7. Continued.

Attribute/Programme Type	Mail	Online
Travel*Public	–	\$484 (462, 506)
Travel*Private	–\$498 (–520, –476)	\$307 (292, 321)
Bachelors*Public	\$832 (796, 868)	\$893 (852, 934)
Bachelors*Private	–	\$530 (506, 555)
Retire*Public	–\$1477 (–1541, –1413)	–\$1047 (–1095, –999)
Retire*Private	–\$748 (–780, –715)	–\$698 (–730, –666)

^aApplying Equation (10) results in slight differences in mean WTP estimates due to rounding. For models having cost as a random variable, individual WTP estimates are calculated to estimate the average WTP.

^bStandard deviation in parentheses.

–Are not reported due to non-significant values.

The underlying similarity of fire risk perception and prior fire experience (i.e. salience), and similar response rates of mail and online surveys might suggest similar parameter and WTP values would be observed. The *risk*, *loss* and *cost* coefficients have the correct negative sign for MNL, RPL and ECLC AN-A models in both survey modes. The *cost* coefficients are statistically significant for all four models in the **online** survey modes, but not significant for LCRPL AN-A in the mail survey mode. Using the MNL and RPL models, three of the interaction variables with forest fuel reduction programme ASCs coefficients for the **mail** survey were statistically significant. For the **online** survey, five of the programme ASC interaction terms were significant in the MNL model, and six in the RPL model were statistically significant.

As previous research has demonstrated, AN-A behaviour can influence coefficient estimates within choice experiments. Therefore, the mail and online models were re-estimated using the ECLC AN-A and LCRPL AN-A models to detect AN-A and examine its impacts on parameters and WTP values. For the LCRPL AN-A model, all interaction variables with forest fuel reduction ASC coefficients are statistically significant in the online survey sample and four of the six in the mail survey sample. For the ECLC AN-A, the online sample has the public and private programme coefficients significant, as well as two interaction variables with forest fuel reduction ASC coefficients, while the mail sample only has the private programme coefficient significant and two interaction variables significant. Based on the goodness-of-fit tests, ECLC AN-A models in both samples performed better than the MNL and RPL models. This suggests that accounting for AN-A can reduce biases in model results by properly modelling respondents' trade-offs. In general, using the ECLC AN-A model, we found that non-attendance occurred in both survey modes regarding the *loss*, *risk* and *cost* attributes. Model estimates indicated that respondents to the mail survey attended somewhat more to *cost* than did respondents to the online survey, while the opposite is found for *loss* and *risk* attributes. Non-attendance to the *cost* attribute by itself was quite low, but much higher when considering the combined non-attendance to *cost*, *loss* and *risk* as a group. When considered as a group, these three had 47.5% non-attendance in the mail sample and 56.5% non-attendance in the online sample. These rates of group non-attendance are somewhat lower compared with non-attendance rates for monetary attributes in prior environmental economic CE studies (Gonçalves et al. 2022). Overall, the different models provide consistent results; the variables have the same signs and, in most cases, have the same statistically significant variables, but magnitudes differ.

An important finding is that accounting for AN-A using the ECLC model made a noticeable improvement in goodness of fit for both survey samples compared with MNL and RPL models. When the ECLC AN-A model is compared with a more complex model that also accounts for attribute non-attendance, LCRPL AN-A, the ECLC AN-A model has a much higher goodness of fit.

This suggests that the simpler model does a good job of accounting for AN-A. Furthermore, the WTP estimates are significantly lower in the ECLC AN-A model than in the other models. This is consistent with other studies that found a decrease in WTP when accounting for AN-A's behaviour (Hensher, Rose, and Greene 2005; Hindsley et al. 2023; Scarpa et al. 2013). Overall, the evidence suggests that respondents in the two survey modes appear to use different heuristics for simplifying their choice decision-making. This suggests that more research needs to be conducted to develop a better understanding of how survey mode affects convergent validity in CE stated preference studies, particularly for natural hazards such as wildfire. Furthermore, understanding the additional types of attributes homeowners focus on when making decisions may help improve participation in fuel mitigation programmes.

The study does have some limitations, in part due to the display of the choice set tasks. By providing the expected ten-year loss (risk $\times$ loss) to enhance respondent understanding of how risk and loss combine to determine expected 10-year loss in the choice set tasks, we may have inadvertently encouraged greater reliance on heuristic decision making, where respondents substituted the expected ten-year loss attribute for the individual risk and loss attributes. Consequently, the AN-A models cannot distinguish whether a respondent truly ignored the individual risk or loss attributes or was simply relying on the pre-calculated expected loss value provided in the survey.

We further recognize that reliance on the expected loss attribute may vary by survey mode. In the mail survey, the physical nature of the survey may have encouraged more deliberate, compensatory processing, potentially reducing reliance on the pre-calculated heuristic. Conversely, online survey respondents who typically exhibit faster survey turnaround times (average of 2.7 days vs 12.2 days for mail survey; see Markovitch 2009) may have more frequently utilized the expected loss attribute as a simplifying heuristic to manage the cognitive demands of the choice tasks. While our current ECLC AN-A model identifies non-attendance patterns, it cannot definitively disentangle whether these patterns reflect true preferences or mode-specific processing strategies induced by the visual aid. This suggests that the lower WTP estimates found in our ECLC AN-A models likely represent a more conservative and accurate reflection of preferences once these heuristic shortcuts are accounted for. The other limitation is the smaller-than-expected sample sizes. The sample size can have an impact on detecting significance in the parameter coefficients, especially in more complex models (e.g. LCRPL AN-A). The sample size for the LCRPL AN-A model may not be large enough for reliable class identification with a high number of classes. This could be a reason for similar ('balanced') class percentages found in our results. Further research may be needed with larger sample sizes to validate our results.

Notes

1. We note that risk-benefit trade-offs are implicit to many healthcare decisions and risk attributes have been included in more than 100 healthcare CE studies (Harrison et al. 2014).
2. The complexity of a CE also increases with the number of alternatives included in the choice design (Swait and Adamowicz 2001; Balbontin, Hensher, and Collins 2017; Grebitus and Roosen 2018). While many CE studies only include one alternative to a status quo alternative, the complexity of this study is increased by including two alternatives to the status quo. AN-A is thus evaluated for attributes and alternatives.
3. <https://www.census.gov/programs-surveys/decennial-census/decade/2020/2020-census-main.html>.
4. <https://www.route-fifty.com/digital-government/2024/04/new-fcc-broadband-standard-increases-number-underserved-households-america/395486/#:~:text=Using%20new%20address%2Dlevel%20deployment, everywhere%20to%20high%2Dspeed%20broadband.>
5. We use *italics* to denote variables used in the empirical analysis.
6. In all of the econometric models we present, the scale parameter is confounded with the β parameters of interest, and therefore we assume that its value is unity. In a single data set, the scale parameter cannot be recovered.
7. As pointed out by a reviewer, using a normal distribution for cost can result in some respondents having positive preferences for higher cost, which is inconsistent with economic theory. There are a couple of ways to

avoid this problem in the RPL model. One is to use a log-normal distribution (with a reversed sign) for cost (Train 2009) or another is using one-sided (constraint) triangular, which is designed to constrain the cost coefficient to negative sign (Greene 2016; Hensher, Rose, and Greene 2015). Another option is to treat cost as a fixed (non-random) variable. The drawback of treating cost as a fixed variable is that it does not take full advantage of the potential of the RPL model. To determine which of these two approaches resulted in a better model fit, as judged by AIC, BIC, McFadden's pseudo R^2 and log-likelihood values, both approaches were tried. The other model results not presented in paper are available from the senior author.

8. While the choice sets included a pre-calculated expected ten-year loss (the product of risk and loss attributes) as a visual aid, this auxiliary information was excluded as an independent attribute in the AN-A estimation to prevent structural redundancy. By omitting this nonlinear combination attribute from the model specification, we avoided having the Hessian matrix become highly sensitive to minor empirical variations that can lead to optimization convergence failures. We acknowledge that the presence of expected loss attribute may have increased the cognitive burden and reliance on heuristic decision making. Consequently, the model cannot definitively distinguish between a respondent who truly ignored risk or loss and one who relied primarily on the provided expected loss value. Nevertheless, the eight-group classification was maintained to ensure model identification while providing a framework to discuss how such heuristic processing might influence inferred attribute non-attendance rates.
9. Several ECLC AN-A models were run, but the model with eight groups has the best model fit. Results of other AN-A models can be requested from senior author.
10. We also estimated alternative AN-A model specification by replacing risk and loss variables with the nonlinear combination of risk and loss (i.e., expected loss) to evaluate specification sensitivity. Overall, we do obtain robust results in the ECLC AN-A models. The expected loss non-attendance (17.97%) is almost the same as the loss & risk non-attendance (17.7%) for online survey and similar pattern is observed in the mail survey 36.2% (expected loss non-attendance) and 37.5% (loss & risk non-attendance). Results are available from senior author.
11. These rates are lower than reported in prior environmental economic studies, where non-attendance to the monetary attribute ranged from 60 to -90% of respondents (Gonçalves et al. 2022).
12. Several models were run with different distributions for the random variables. The model reported in manuscript was selected based on goodness of fit criteria. The results not presented in paper are available from the senior author.

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Author contributions

CRedit: **José J. Sánchez:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Methodology, Project administration, Visualization, Writing – original draft, Writing – review & editing; **Thomas P. Holmes:** Conceptualization, Methodology, Visualization, Writing – original draft, Writing – review & editing; **John B. Loomis:** Conceptualization, Methodology, Visualization, Writing – original draft, Writing – review & editing.

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References

- Alho, E. 2017. "Attention to Risk and Return: Choice Experiment of the Stated and Inferred Use of Investment Attributes." *Applied Economics and Finance* 4 (1): 43–52.
- Balbontin, C., D. A. Hensher, and A. T. Collins. 2017. "Integrating Attribute non-attendance and Value Learning with Risk Attitudes and Perceptual Conditioning." *Transportation Research Part E: Logistics and Transportation Review* 97:172–191. <https://doi.org/10.1016/j.tre.2016.11.002>.
- Balcombe, K., M. Bitzios, I. Fraser, and J. Haddock-Fraser. 2014. "Using Attribute Importance Rankings within Discrete Choice Experiments: An Application to Valuing Bread Attributes." *Journal of Agricultural Economics* 65:446–462. <https://doi.org/10.1111/1477-9552.12051>.
- Bayham, J., J. K. Yoder, P. A. Champ, and D. E. Calkin. 2022. "The Economics of Wildfire in the United States." *Annual Review of Resource Economics* 14:379–401. <https://doi.org/10.1146/annurev-resource-111920-014804>.
- Boyle, K. J., M. Morrison, D. H. MacDonald, R. Duncan, and J. Rose. 2016. "Investigating Internet and Mail Implementation of Stated-Preference Surveys While Controlling for Differences in Sample Frames." *Environmental and Resource Economics* 64:401–419. <https://doi.org/10.1007/s10640-015-9876-2>.
- Campbell, R. M., T. J. Venn, and N. M. Anderson. 2018. "Cost and Performance Tradeoffs between Mail and Internet Survey Modes in a Nonmarket Valuation Study." *Journal of Environmental Management* 210:316–327. <https://doi.org/10.1016/j.jenvman.2018.01.034>.
- Caputo, V., E. J. Van Loo, R. Scarpa, R. M. Nayga, Jr., and W. Verbeke. 2018. "Comparing Serial, and Choice Task Stated and Inferred Attribute Non-Attendance Methods in Food Choice Experiments." *Journal of Agricultural Economics* 69 (1): 35–57. <https://doi.org/10.1111/1477-9552.12246>.
- Champ, P.A., K. Boyle, and T. C. Brown. 2017. *A Primer on Nonmarket Valuation*. 2nd ed. Springer, Netherlands.
- Colorado State Forest Service. 2018. 2017 Colorado wildfire risk assessment update. Accessed April 3, 2020. <https://www.coloradowildfirerisk.com/>.
- Couper, M. P. 2000. "Web Surveys." *Public Opinion Quarterly* 64 (4): 464–494. <https://doi.org/10.1086/318641>.
- Daikeler, J., M. Bošnjak, and K. Lozar Manfreda. 2020. "Web versus Other Survey Modes: An Updated and Extended Meta-analysis Comparing Response Rates." *Journal of Survey Statistics and Methodology* 8 (3): 513–539. <https://doi.org/10.1093/jssam/smz008>.
- Determann, D., M. S. Lambooi, E. W. Steyerberg, E. W. de Bekker- Grob, and G. A. De Wit. 2017. "Impact of Survey Administration Mode on the Results of a Health-Related Discrete Choice Experiment: Online and Paper Comparison." *Value in Health* 20:953–960. <https://doi.org/10.1016/j.jval.2017.02.007>.
- Dillman, D. A., J. D. Smyth, and L. M. Christian. 2014. *Internet, Phone, Mail, and Mixed-Mode Surveys. The Tailored Design Method*. 4th ed. Hoboken, New Jersey: John Wiley & Sons, Inc.
- Econometric Software, Inc. 2016. Statistical & Data Analysis Software | LIMDEP | NLOGIT Statistical & Data Analysis Software | LIMDEP | NLOGIT. <https://www.nlogit.com>
- ESOMAR. 2018. Global Market Research Report 2018: An ESOMAR Industry Report.
- Fricker, R. D., and M. Schonlau. 2002. "Advantages and Disadvantages of Internet Research Surveys: Evidence from the Literature." *Field Methods* 14 (4): 347–367. <https://doi.org/10.1177/152582202237725>.
- Glenk, K., J. Martin-Ortega, M. Pulido-Velazquez, and J. Potts. 2015. "Inferring Attribute non-attendance from Discrete Choice Experiments: Implications for Benefit Transfer." *Environmental and Resource Economics* 60 (4): 497–520.
- Gonçalves, T., L. Lourenço-Gomes, Costa Pinto, and L. M. 2022. "The Role of Attribute non-attendance on Consumer Decision-Making: Theoretical Insights and Empirical Evidence." *Economic Analysis and Policy* 76:788–805. <https://doi.org/10.1016/j.eap.2022.09.017>.
- González-Cabán, A., and J. J. Sánchez. 2017. "Minority Households' Willingness to pay for Public and Private Wildfire Risk Reduction in Florida." *International Journal of Wildland Fire* 26:744–753. <https://doi.org/10.1071/WF16216>.
- Goodrich, B., M. Fenton, J. Penn, J. Bovay, and T. Mountain. 2023. "Battling Bots: Experiences and Strategies to Mitigate Fraudulent Responses in Online Surveys." *Applied Economic Perspectives and Policy* 45:762–784. <https://doi.org/10.1002/aep.13353>.
- Grebitus, C., and J. Roosen. 2018. "Influence of non-attendance on Choices with Varying Complexity." *European Journal of Marketing* 52:2151–2172. <https://doi.org/10.1108/EJM-02-2017-0143>.
- Greene, W. H. 2016. *NLogit Version 6 Reference Guide*. New York, NY: Econometric Software, Inc.
- Harrison, M., D. Rigby, C. Vass, T. Flynn, J. Louviere, and K. Payne. 2014. "Risk as an Attribute in Discrete Choice Experiments: A Systematic Review of the Literature." *The Patient – Patient-Centered Outcomes Research* 7:151–170. <https://doi.org/10.1007/s40271-014-0048-1>.
- Hensher, D. A., J. M. Rose, and W. H. Greene. 2005. "The Implications on Willingness to pay of Respondents Ignoring Specific Attributes." *Transportation* 32 (3): 203–222. <https://doi.org/10.1007/s11116-004-7613-8>.
- Hensher, D. A., J. M. Rose, and W. H. Greene. 2015. *Applied Choice Analysis*. Cambridge: Cambridge University Press.
- Hess, S., and D. A. Hensher. 2010. "Using Conditioning on Observed Choices to Retrieve Individual-Specific Attribute Processing Strategies." *Transportation Research Part B: Methodological* 44 (6): 781–790. <https://doi.org/10.1016/j.trb.2009.12.001>.

- Hess, S., A. Stathopoulos, D. Campbell, V. O'Neill, and S. Caussade. 2013. "It's Not That I Don't Care, I Just Don't Care Very Much: Confounding between Attribute non-attendance and Taste Heterogeneity." *Transportation* 40:583–607. <https://doi.org/10.1007/s11116-012-9438-1>.
- Hindsley, P., G. E. Landry, K. Schnier, J. C. Whitehead, and M. Zarei. 2023. "Joint Estimation of Angler Revealed Preference Site Selection and Stated Preference Choice Experiment Recreation Data considering Attribute non-attendance." *Journal of Environmental Economics and Policy* 12 (1): 44–62. <https://doi.org/10.1080/21606544.2022.2077840>.
- Holmes, T. P., W. L. Adamowicz, and F. Carlsson. 2017. "Choice Experiments." In *A Primer on Nonmarket Valuation*, edited by P. A. in Champ, K. J. Boyle, and T. C. Brown, 2nd ed. 133–186. Dordrecht, Netherlands: Springer.
- Holmes, T. P., A. González-Cabán, J. Loomis, and J. Sánchez. 2013. "The Effects of Personal Experience on Choice-Based Preferences for Wildfire Protection Programs." *International Journal of Wildland Fire* 22:234–245. <https://doi.org/10.1071/WF11182>.
- Krupnick, A., A. Alberini, M. Cropper, N. Simon, B. O'Brien, R. Goeree, and M. Heintzelman. 2002. "Age, Health and the Willingness to pay for Mortality Risk Reductions: A Contingent Valuation Survey of Ontario Residents." *Journal of Risk and Uncertainty* 24:161–186. <https://doi.org/10.1023/A:1014020027011>.
- Lew, D. K., and J. C. Whitehead. 2020. "Attribute Non-attendance as an Information Processing Strategy in Stated Preference Choice Experiments: Origins, Current Practices, and Future Directions." *Marine Resource Economics* 35 (3): 285–317. <https://doi.org/10.1086/709440>.
- Li, L., and A. W. Ando. 2023. "Early Exposure to Nature and Willingness to Pay for It: The Value of Tallgrass Prairie Grassland Restoration." *Land Economics* 99 (4): 509–527. <https://doi.org/10.3368/le.99.4.070822-0054R>.
- Loomis, J., and P. duVair. 1993. "Evaluating the Effect of Alternative Risk Communication Devices on Willingness to Pay: Results from a Dichotomous Choice Contingent Valuation Experiment." *Land Economics* 69:287–298. <https://doi.org/10.2307/3146594>.
- Markovitch, D. G. 2009. "Comparing Online and Mail Methods in a Sample of Chief Marketing Officers." *Innovative Marketing* 5 (4): 55–62.
- Mjelde, J. W., T. Kim, and C. Lee. 2016. "Comparison of Internet and Interview Survey Modes When Estimating Willingness to pay Using Choice Experiments." *Applied Economics Letters* 23 (1): 74–77. <https://doi.org/10.1080/13504851.2015.1051648>.
- Nayak, M. S. D. P., and K. A. Naraya. 2019. "Strengths and Weaknesses of Online Surveys." *IOSR Journal of Humanities and Social Sciences* 24 (5): 31–38.
- Olsen, S. B. 2009. "Choosing between Internet and Mail Survey Modes for Choice Experiment Surveys considering non-market Goods." *Environmental and Resource Economics* 44:591–610. <https://doi.org/10.1007/s10640-009-9303-7>.
- Petrolia, D. R., and J. Hwang. 2020. "Accounting for Attribute non-attendance in Three Previously Published Choice Studies of Coastal Resources." *Marine Resource Economics* 35 (3): 219–240. <https://doi.org/10.1086/709442>.
- Poe, G. L., K. L. Giraud, and J. B. Loomis. 2005. "Computational Methods for Measuring the Difference of Empirical Distributions." *American Journal of Agricultural Economics* 87 (2): 353–365. <https://doi.org/10.1111/j.1467-8276.2005.00727.x>.
- Rose, J. M., A. T. Collins, M. C. Bliemer, and D. A. Hensher. 2014. Ngene 1.1.2 stated choice experiment design software. <http://www.choice-metrics.com/index.html>
- Sánchez, J. J., T. P. Holmes, J. Loomis, and A. González-Cabán. 2022. "Homeowners Willingness to pay to Reduce Wildfire Risk in Wildland Urban Interface Areas: Implications for Targeting Financial Incentives." *International Journal of Disaster Risk Reduction* 68:102696. <https://doi.org/10.1016/j.ijdrr.2021.102696>.
- Scarpa, R., T. J. Gilbride, D. Campbell, and D. A. Hensher. 2009. "Modelling Attribute non-attendance in Choice Experiments for Rural Landscape Valuation." *European Review of Agricultural Economics* 36 (2): 151–174. <https://doi.org/10.1093/erae/jbp012>.
- Scarpa, R., M. Thiene, and D. A. Hensher. 2010. "Monitoring Choice Task Attribute Attendance in Nonmarket Valuation of Multiple Park Management Services: Does It Matter?" *Land Economics* 86 (4): 817–839. <https://doi.org/10.3368/le.86.4.817>.
- Scarpa, R., R. Zanolì, V. Bruschi, and S. Naspètti. 2013. "Inferred and Stated Attribute Non-Attendance in Food Choice Experiments." *American Journal of Agricultural Economics* 95 (1): 165–180. <https://doi.org/10.1093/ajae/aas073>.
- Shih, T.-H., and X. Fan. 2009. "Comparing Response Rates in e-Mail and Paper Surveys: A Meta-analysis." *Educational Research Review* 4:26–40. <https://doi.org/10.1016/j.edurev.2008.01.003>.
- Shin, E., T. P. Johnson, and K. Rao. 2012. "Survey Mode Effects on Data Quality: Comparison of Web and Mail Modes in a U.S. National Panel Survey." *Social Science Computer Review* 30 (2): 212–228. <https://doi.org/10.1177/0894439311404508>.
- Smith, V. K., and W. Desvousges. 1987. "An Empirical Analysis of the Economic Value of Risk Changes." *Journal of Political Economy* 95:89–114. <https://doi.org/10.1086/261443>.

- Swait, J., and W. Adamowicz. 2001. "Choice Environment, Market Complexity, and Consumer Behavior: A Theoretical and Empirical Approach for Incorporating Decision Complexity into Models of Consumer Choice." *Organizational Behavior and Human Decision Processes* 86:141–167. <https://doi.org/10.1006/obhd.2000.2941>.
- Train, K. 2009. *Discrete Choice Methods with Simulation*. 2nd ed. Cambridge: Cambridge University Press.
- Watson, V., T. Porteous, T. Bolt, and M. Ryan. 2019. "Mode and Frame Matter: Assessing the Impact of Survey Mode and Sample Frame in Choice Experiments." *Medical Decision Making* 39 (7): 827–841. <https://doi.org/10.1177/0272989X19871035>.
- Windle, J., and J. Rolfe. 2011. "Comparing Responses from Internet and Paper-Based Collection Methods in More Complex Stated Preference Environmental Valuation Surveys." *Economic Analysis and Policy* 41 (1): 83–97. [https://doi.org/10.1016/S0313-5926\(11\)50006-2](https://doi.org/10.1016/S0313-5926(11)50006-2).