

Minority households' willingness to pay for public and private wildfire risk reduction in Florida

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Abstract. The purpose of this work is to estimate willingness to pay (WTP) for minority (African-American and Hispanic) homeowners in Florida for private and public wildfire risk-reduction programs and also to test for differences in response between the two groups. A random parameter logit and latent class model allowed us to determine if there is a difference in wildfire mitigation program preferences, whether WTP is higher for public or private actions for wildfire risk reduction, and whether households with personal experience and who perceive that they live in higher-risk areas have significantly higher WTP. We also compare Florida minority homeowners' WTP values with Florida original homeowners' estimates. Results suggest that Florida minority homeowners are willing to invest in public programs, with African-Americans WTP values at a higher rate than Hispanics. In addition, the highest priority for cost-sharing funds would go to low-income homeowners, especially to cost-share private actions on their own land. These results may help fire managers optimise allocation of scarce cost-sharing funds for public v. private actions.

Additional keywords: choice experiment, Firewise, latent class model, random parameter logit model, WUI.

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Introduction

In recent years, the United States has seen an increase in the number and severity of wildland fires due to growing fire seasons, drier conditions and accumulation of fuels. From 2000 to 2013, wildfires affected over 3.7×10^7 ha of forest and brush lands and federal fire protection agencies spent almost US\$2 billion in suppression cost (National Interagency Fire Center Wildland Fire Statistics 2014). Costs in the present report are all reported in US dollars. Fire suppression expenditures for the first time in the 2015 fiscal year exceeded 50% of USDA Forest Service (USFS) budget.

Wildland fires represent a threat to many communities nationwide. However, residential neighbourhoods located in the wildland–urban interface (WUI, the area where houses and undeveloped wildland vegetation meet) are prone to higher risk for loss of life and property (For a more complete definition of the term see Radeloff *et al.* 2005). Increases in wildfire risks have led the USFS and state and local agencies to develop cost-shared programs with communities and private homeowners (e.g. Firewise communities programs). These programs provide direct payment for fuel reduction efforts on public and private lands surrounding many of these communities. These programs, however, are costly to private homeowners and federal, state and county fire management agencies. Given current funding limitations, it is important for the USFS and state agencies to know the benefits of these fire risk-reduction programs.

Several contingent valuation method (CVM) survey studies have been done throughout the USA on how much money

households would pay to state and county agencies for funding wildfire reduction projects. For example, Fried *et al.* (1999) found that most Michigan residents expressed positive willingness to pay (WTP) for publicly funded risk-reduction activities. Loomis and González-Cabán (2010) surveyed households in California, Florida and Montana and found that the mean WTP per household for prescribed burning was \$460, \$392 and \$323 respectively. They also found that the mean WTP per household for mechanical fuel reduction was \$510, \$239 and \$189. Walker *et al.* (2007) used CVM to compare Colorado WUI residents' WTP for prescribed burning v. thinning. They found that for Boulder and Larimer counties, WUI residents' WTP was higher for a thinning program (\$443 and \$311 respectively) than prescribed burning (\$202 and \$150 respectively). Similar results were found by Kaval *et al.* (2007) and Meldrum *et al.* (2014) from survey data of Colorado WUI residents. Kaval *et al.* (2007) found that mean WTP for prescribed burning was nearly \$800 per year, whereas Meldrum *et al.* (2014) estimated the mean WTP for vegetation removal to range from \$460 to \$480 per acre. More recently, J. J. Sánchez, J. Loomis, A. González-Cabán and T. P. Holmes (unpubl. data) used a choice experiment survey to determine California homeowners' preferences and WTP for public and private wildfire mitigation programs. The authors found that California homeowners who perceived they were living in a high-risk community had WTP for a 10-year public and private program of \$1265 and \$1733 respectively.

However, few studies have studied minority households' WTP for fuel treatment projects. A study by Loomis *et al.* (2009)

used voter referendum survey questions to compare California, Florida and Montana White and Hispanic households' WTP for prescribed burning and mechanical fire fuel reduction programs. Pooling the data from the three states into one model for each fire fuel reduction program, the authors found that the marginal benefits for prescribed burning (mechanical) fuel treatment of 1 million White households was \$2578 (\$3376) per acre (0.405 ha), whereas the marginal benefits for 1 million Hispanic households would be higher, \$10 121 (\$31 279).

In a recent study by Holmes *et al.* (2013) of Florida homeowners' preferences and WTP for wildfire protection programs, fewer than 10% of survey participants were minorities (African-American and Hispanic). However, 28.9% of the Florida population are of Hispanic and African-American descent (US Census Bureau 2015). Therefore, their results are based on a segment of the Florida population and results may not be representative of the entire state. The present study expands the study of Holmes *et al.* (2013) by focusing on the missing minority population. The significant increase in Florida minority population from 2010 to 2015 highlights the importance of including these populations when considering households' WTP for evaluating fuel treatment reduction programs. In the period from 2010 to 2015, the African-American population in the state increased by 11.7% from 3 008 740 to 3 405 574. For the same period, the Hispanic population increased by 14.8%, going from 4 231 037 to 4 966 462, and although the White population increased by 2.95% for the period, their percentage of the total state population decreased from 57.9 to 55.3% (US Census Bureau 2015).

Preferences in wildfire management can differ by cultural and ethnic group. Bowker *et al.* (2008) found differences in fire management opinions across race and ethnicity; African-Americans had higher levels of concern than both Whites and Hispanics. Furthermore, involvement with wildfire mitigation programs can be reflected by racial or geographic biases (Gaither *et al.* 2011). This research is useful to understand the factors that influence minority decisions of whether, and how much, to invest in wildland fire hazard mitigation programs and whether African-American and Hispanics respond differently to these programs. Results from the present study can potentially help identify the type of wildfire mitigation program preferred by each race and ethnicity group. In addition, the research could also help fire managers to identify obstacles to the implementation of efficient fire mitigation programs and policies.

The present study contributes to the literature by implementing a choice experiment to understand trade-offs minority (African-American and Hispanic) households are willing to make between fire mitigation programs. We replicated the study of Holmes *et al.* (2013) by using the same choice experiment survey, but focusing only on Florida minority homeowners to estimate WTP for private and public wildfire risk-reduction programs. We valued two fire risk-reduction programs: (1) a public program carried out by public forest managers that involves prescribed burning, mechanical treatment and herbicide treatment of forests immediately surrounding the residents' neighbourhood; and (2) a private program that alters the vegetation surrounding the home, such as reducing tall vegetation (more than 3 feet high, ~0.914 m) within 30 feet (~9.144 m) of their house (see www.firewise.org for more information on the private program, accessed 23 April

2016). A random parameter logit model and latent class model allowed us to determine whether minorities' WTP is higher for public or private actions for wildfire risk reduction, and whether households with personal experience and perceiving they live in higher-risk areas have significantly higher WTP. We assessed residents' preferences for wildfire mitigation programs and explored the heterogeneity of those preferences. In addition, analyses were done to ascertain if African-American and Hispanic households responded differently to WTP for wildfire mitigation programs.

The paper proceeds as follows: first, we introduce the choice experiment method, random parameter logit and the latent class model specification, followed by presentation of the choice experiment survey design. Then, we describe the data and present the econometric results. In the final section, we present our conclusions.

Econometric models of choice experiment responses

Choice models describe an individual's choices among alternatives (Train 2009). The choice experiment (CE) method has been widely used in marketing and transportation literature to analyse consumer choice of products, modes of travel and other items (Adamowicz *et al.* 1998). This method can also estimate economic values (individual's WTP) for a set of attributes of environmental goods and services (Boxall *et al.* 1996).

The CE method provides detailed information about public preferences on environmental goods and services. The survey presented to respondents includes hypothetical scenarios describing specific issues along with a description of attributes. Individuals are given choice sets, each of which usually consist of three alternatives (one must be the status quo or opt-out option) to evaluate. The status-quo option was included as a choice representing a typical current situation with no cost to homeowners and it assumes no additional wildfire mitigation measure would be applied. The individuals must select the alternative from the choice set that best reflects their preference. Resource managers and policy-makers may use this added information (individuals' preferred attributes) to inform decisions on environmental goods and services.

The CE method is based on the random utility theory and random utility theory uses the principle of utility maximisation. Random utility models (RUM) describe discrete choices in utility-maximising frameworks. It is assumed that individuals select goods that provide the greatest utility among those available to them (Champ *et al.* 2003).

RUM assumes that the utility is the sum of a deterministic (V_{ni}) and stochastic components (ε_{ni}):

$$U_{ni} = V_{ni} + \varepsilon_i \sum_{k=1}^K \beta_{nk} x_{nik} + \varepsilon_{ni} \quad (1)$$

where U_{ni} is unobserved utility associated with individual n after selecting alternative i , x_{nik} is the vector of K attributes for alternative i and individual n , β_{nk} is the vector of preference parameters, and ε_i is the random error term. Logit models assume the error term is independently and identically distributed. Depending on the assumption made on the error term, different probabilistic choice models can be derived (Champ

et al. 2003). We can set the probability of individual n choosing alternative i from the set Θ as:

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

where μ is a scale parameter that is typically set equal to one (this section relies on J. J. Sánchez, J. Loomis, A. González-Cabán and T. P. Holmes (unpubl. data)). 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 dataset, the scale parameter cannot be recovered.

The Random Parameter Logit (RPL) model, often called Mixed Logit model, is a generalisation of the multinomial logit model (MNL) model, and allows for random variation in preferences, flexible substitution patterns and correlations among unobserved factors (Train 2009). By using the RPL model, we may relax the independence of irrelevant alternatives assumption by introducing additional stochastic components to the utility function through β_n . These components allow the preference parameters for the x_{nik} 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. However, this is true only when the marginal utilities are assumed to be normally distributed across respondents and correlation of preferences across attributes is permitted.

In the RPL model, probabilities 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 $f(\beta)$. Let π_{ni} be the probability that an individual n chooses alternative i from set I , such that

$$\pi_{ni} = \int \left(L_{ni}(BX_i) f(\beta|\theta) d\beta \right) \quad (4)$$

where

$$L_{ni}(\beta X_i) = \frac{\exp(\mu\beta X_{ni})}{\sum_{i=1}^I \exp(\mu\beta X_{ni})} \quad (5)$$

The function $f(\beta|\theta)$ can then be simulated using random draws from various functional forms (Train 2009). We use 500 Halton draws from the normal distribution to estimate Γ for the random parameters in the RPL model. The RPL model captures heterogeneity by a continuous probability distribution for preference parameters.

We use a latent class model (LCM) to capture preference heterogeneity for a finite number of heterogeneity classes (Boxall and Adamowicz 2002; Scarpa and Thiene 2005) and use this model to compare Florida minorities with Florida

households in the original study (Holmes *et al.* 2013). The LCM assumes the existence of C classes (or groups) in a population with individual n belonging to class c . Individuals within a class are assumed to have homogeneous preferences. The specific utility parameter for each class and the choice probabilities for alternative i for each class are:

$$\pi_{n|c}(i) = \frac{\exp(\mu_c \beta_c X_{ni})}{\sum_{k \in C} \exp(\mu_c \beta_c X_{nk})} \quad (6)$$

where C is the set of all classes. The probability that an individual n belongs to class c often is assumed to be logistic:

$$\pi_{nc} = \frac{\exp(\alpha \gamma_c Z_n)}{\sum_{c=1}^C \exp(\alpha \gamma_c Z_n)} \quad (7)$$

where α is a scale parameter (set equal to one), γ_c are specific class-related coefficients, and Z is a vector of an individual's sociodemographics and other individual characteristics. The joint probability that an individual n belongs to class c and selects alternative i can be written as the product of Eqns 6 and 7:

$$\pi_n(i) = \sum_{c=1}^C \left(\pi_{nc} \pi_{n|c} \right) \quad (8)$$

Table 1. Random parameter logit model estimates of preference parameters for wildfire hazard mitigation programs with random parameters estimated for risk, loss, and risk $\times$ loss interaction variables The dependent variable is the alternative selected in the choice questions. Note: standard errors in parentheses. Statistical significance is indicated by **, <0.05; ***, <0.01

Variable	Random parameter Logit model	
	mean	(s.d.)
Risk (%)	0.3537*** (0.0585)	0.0098 (2.4832)
Loss (\$1000)	0.0171*** (0.0031)	0.0002 (0.1737)
Risk $\times$ loss	0.8442*** (0.2376)	1.6686*** (0.0963)
Cost (\$)	0.0004*** (0.0001)	–
Hispanic dummy $\times$ cost	0.0005** (0.0002)	–
Public program	1.4254*** (0.2510)	–
Public program $\times$ high risk	1.3764*** (0.5201)	–
Private program	1.0640*** (0.2509)	–
Private pro. $\times$ high risk	1.1347 (0.7578)	–
Hispanic dummy $\times$ public	1.0586*** (0.3864)	–
Hispanic dummy $\times$ private	0.8211** (0.3916)	–
n	319	–
McFadden R^2	0.1941	–
Log-likelihood	847.28	

The parameter estimates are estimated by maximising the log-likelihood function:

$$\ln L = \sum_{j=1}^J \ln \sum_{c=1}^C \left(\pi_{nc} \prod_{i=1}^I \left(\pi_{ni|c} \right)^{y_{ji}} \right) \quad (9)$$

This model specifies that the choice of an alternative is based on the attributes and respondents' characteristics.

In a choice experiment, the implicit prices (marginal WTP [MWTP] estimates) of the attributes are measured by the parameter coefficient divided by the absolute value of the cost coefficient.

$$\text{MWTP} = \frac{\beta_{\text{program type}}}{|\beta_{\text{cost}}|} \quad (10)$$

Using this formula and the wildfire hazard mitigation program and cost parameter estimates from RPL and LC models (Tables 1, 2), the one-time mean WTP for 10-year public and private programs can be derived.

Choice experiment survey design

We used the same survey as Holmes *et al.* (2013), which was available both in English and Spanish. The survey began with

several questions that asked respondents about the vegetation around their home. These questions were followed by a characterisation of what certain responses meant for the risk of wildfire in their neighbourhood, and the risk of losing their house to a wildfire. Using Florida fire statistics, the current wildfire risk was characterised using a risk ladder and risk chance grid. The chance of a home being damaged by a wildfire is represented in the chance grid by the number of red squares on a 1000-cell square grid. The remaining white squares (Fig. 1) represent the risk of the house being undamaged. A risk ladder (Fig. 2) was presented to respondents as a way to convey the risk of a wildfire damaging a home relative to other ordinary risks (such as having a heart attack for a person over 35 years of age). Both of these risk communication devices have been used in past surveys as a way to convey to respondents relative and absolute risks (Smith and Desvousges 1987; Loomis and duVair 1993; Krupnick *et al.* 2002).

The survey implemented a full factorial randomised experimental design (see Holmes *et al.* 2013) to construct the choice sets. The choice experiment used four attributes (Table 3) of the survey: (1) *risk* (%) or chance (out of 1000) of your house being damaged by wildfires in the next 10 years; this risk varied over five levels, from 1 to 5%, where 5% was the baseline risk respondents were told was associated with no new investments in wildfire protection programs (we use italic format to denote variables used in the

Table 2. Latent class model estimates of homeowner preference parameters for wildfire hazard mitigation programs among survey respondents

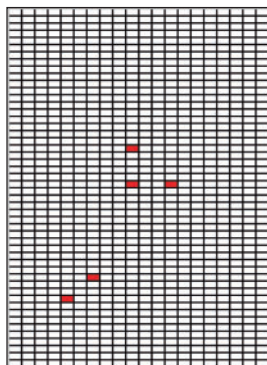
For the two-class model (FL original), we used data from Holmes *et al.* (2013) to run the same model as the FL minorities by removing public program and defensible space interaction and added low-income households to membership class to make comparisons. This model result was not included or published in Holmes *et al.* (2013). Note: standard errors in parentheses. * indicates significance at the 0.10 level, ** indicates significance at the 0.05 level, *** indicates significance at the 0.01 level

Variable	Two-class model (FL minority)		Two-class model (FL original)	
	Class 1	Class 2	Class 1	Class 2
<i>Risk</i> (%)	0.1327 (0.1305)	0.1158** (0.0450)	0.0006 0.0878	0.1135*** 0.0263
<i>Loss</i> (\$1000)	0.0150** (0.0066)	0.0051** (0.0022)	0.0087* 0.0045	0.0041*** 0.0013
<i>Cost</i> (\$)	0.0016*** (0.0005)	0.0005*** (0.0001)	0.0027*** 0.0007	0.0007*** 0.0001
<i>Public pro.</i>	0.9914** (0.4461)	2.6046*** (0.3086)	2.3987*** 0.3687	2.1513*** 0.1686
<i>Public program</i> × <i>high risk</i>	0.5144 (0.9434)	1.7873** (0.8765)	1.6088*** 0.4308	0.8766 0.5536
<i>Private program</i>	1.3466*** (0.4931)	2.2046*** (0.3117)	2.5376*** 0.3996	1.8884*** 0.1712
<i>Private program</i> × <i>high risk</i>	1.3904 (0.9209)	1.5519* (0.8985)	0.6006 1.0945	1.1766** 0.5611
Covariates explaining latent class membership ^A				
<i>Constant</i>	0.6672*** (0.2193)	—	0.2916** 0.1178	—
<i>Personal experience</i>	0.5012* (0.2844)	—	0.5806*** 0.1463	—
<i>Low-income households</i>	0.4299* (0.2548)	—	0.0666 0.1451	—
Class membership probability	0.36	0.64	0.38	0.62
<i>n</i>	319		922	
McFadden <i>R</i> ²	0.227		0.243	

^AIn the two-class model, Class 2 is the baseline.

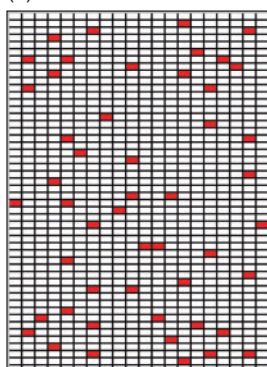
CHANCE GRIDS

(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 neighbourhood. 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: 10-year chance



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

Fig. 1. Risk grids to convey relevant degree of wildfire risk to homeowner survey participants (used with permission from Holmes *et al.* 2013).

empirical analysis); (2) monetary damage (*loss*) to property from the wildfire; the *loss* varied over 10 levels that ranged from \$10 000 to \$100 000; (3) expected 10-year loss = chance damage; attribute no. 3 is not an independent attribute and was included only to facilitate understanding of how risk and damage interacted to give an 'expected value' of the damages; and (4) one-time *cost* to the household for the 10-year program that varied over 10 levels from \$25 to \$1500 for the public program and 9 levels from \$50 to \$1500 for the private program.

An example of a choice question used in the questionnaire is shown in Table 4. Three alternatives were given in each choice set. The first two alternatives represented public and private fire risk mitigation programs. Each alternative program included chance of damage to the respondent's house, monetary amount of damage, expected loss (chance damage) and a one-time cost for implementing the selected 10-year program. In addition, a status quo alternative was included at no cost, representing the typical current situation. This status quo alternative was provided for each choice scenario. A series of three choice questions were asked of each respondent, resulting in the panel nature of the response data.

Data

A stratified random sample of households was drawn from the population of African-American and Hispanic households in Florida. The assumption for the stratified sample was because

we thought that people living in areas that have a higher risk of damage from wildfires would be both more aware and more concerned regarding wildfire mitigation programs; we developed a weighting scheme where, for each household sampled from low-risk communities (as defined by the Florida State Fire Management Agency), two households were sampled from medium-risk communities and three households were sampled from high-risk communities. Households were recruited using random digit dialling, and basic information was recorded during the initial phone call, as well as identifying if they were African-American or Hispanic. For the interviews, we used African-American interviewers to conduct interviews with African-American respondents and Spanish-speaking interviewers to conduct interviews with Hispanic interviewees. Then, households that were willing to participate in the survey were mailed a survey booklet. Two weeks after mailing the booklet, a postcard reminder was sent to households. Out of 500 subjects recruited for participation, 319 completed the survey interview for an effective response rate of 63.8%.

Results

Table 5 shows the descriptive statistics for variables in our survey sample (FL minority) and data (FL original study) in Holmes *et al.* (2013). The FL minority sample consisted of 63% African-American and 37% Hispanic respondents. The

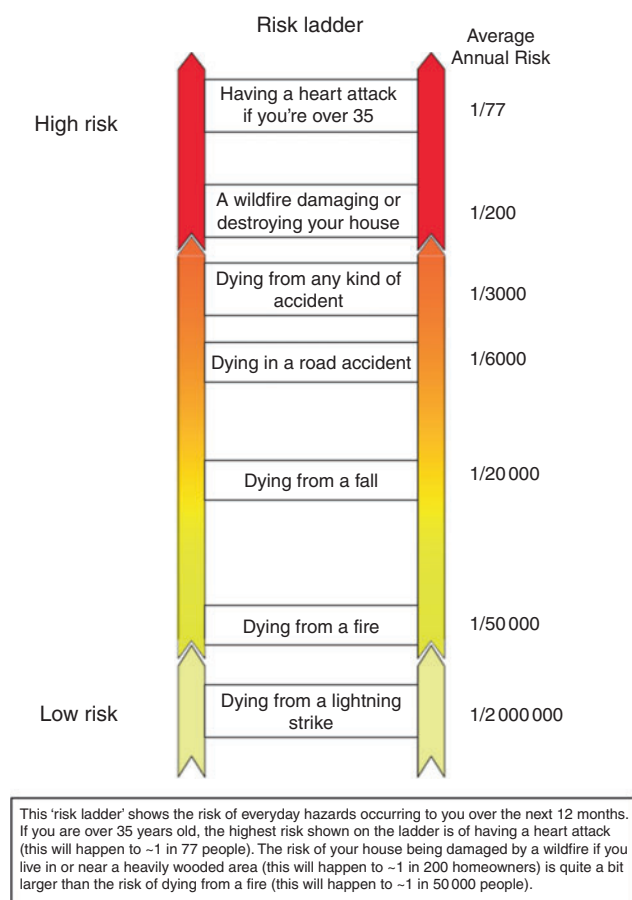


Fig. 2. Risk ladder to illustrate to survey participants the risk of wildfires relative to other, ordinary daily events (used with permission from Holmes *et al.* 2013).

stratified sample included a substantial proportion of respondents with personal experience of the effect of wildfire (31%). A total of 12% of respondents reported health effects from smoke produced by wildfires and 27% reported that they had revised travel plans because of wildfires. Given that 28% of our sample are from communities identified as being at high risk for wildfires, it is surprising that only ~5% of respondents reported that they lived in an area that they perceived to be at high risk for wildfires. It is possible that the reason for this is that the majority of respondents who perceive they live in a high-risk community feel safe based on recent wildfire mitigation activities. Approximately 72% (Firewise) of respondents indicated that they previously improved the defensible space on their property (trimmed lower branches on tree, 58%; removed vines from trees, 50%; removed branches over home, 53%; removed trees and flammable plants, 36%).

In addition, Table 5 shows the variables that are statistically significantly different in the two datasets (FL minorities and FL original study). Using the FL minority dataset to compare African-Americans and Hispanics, we find that a higher percentage of African-Americans have been affected by wildfires. We also found that the difference in income between Hispanic and African-American households is statistically significant.

In the present paper, we focus on the RPL model to compare African-American and Hispanic homeowners' wildfire risk reduction program preferences and the LC model to compare FL minority homeowners' WTP estimates with FL original homeowners' data.

Before starting the analysis, we conducted a likelihood ratio test to test whether we should separate the FL minorities' dataset by ethnicity or keep it as one dataset. Results suggested that we should have only one model, keeping one dataset for minorities. Using the basic MNL, we can include preference heterogeneity by studying the interaction of the choice set attributes with respondent characteristics, but this model cannot account for

Table 3. Attribute levels

Attribute	Levels
Chance of your house being damaged in 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 public program	\$25, \$50, \$100, \$200, \$400, \$600, \$800, \$1000, \$1300 and \$1500
One-time cost to you for the 10-year private program	\$50, \$100, \$200, \$400, \$600, \$800, \$1000, \$1300 and \$1500

Table 4. Example of the choice set

	Alternative 1 Public fire prevention	Alternative 2 Private fire prevention	Alternative 3 Do nothing additional
Chance of your house being damaged in next 10 years	10 in 1000 (1%)	25 in 1000 (2.5%)	50 in 1000 (5%)
Damage to property	\$10 000	\$50 000	\$100 000
Expected 10-year loss = Chance damage	\$100 during 10 years	\$1250 during 10 years	\$5000 during 10 years
One-time cost to you for the 10-year program	\$100	\$500	\$0
I would choose: please check one box	☐	☐	☐

Table 5. Variables descriptive statisticsHispanic data are based on FL minority dataset and FL original homeowners' dataset from Holmes *et al.* (2013)

Variable	Description	African American; Hispanic Mean (s.d.)	FL minority Mean (s.d.)	FL original Mean (s.d.)
Health (dummy variable)	Health of respondent or family member suffered from breathing smoke from wildfire; if Yes = 1; else = 0	0.12 (0.32); 0.13 (0.34)	0.12 (0.33)	0.15 (0.35)
Travel ^{A,C} (dummy variable)	Household travel plans changed because of a wildfire; if Yes = 1; else = 0	0.32 (0.47); 0.18 (0.39)	0.27 (0.44)	0.35 (0.48)
Personal experience ^{A,C} (dummy variable)	If either (health = 1 or travel = 1) = 1; else = 0	0.36 (0.48); 0.23 (0.42)	0.31 (0.46)	0.43 (0.50)
Firewise (dummy variable)	Household conducted at least one activity to reduce wildfire risk; if Yes = 1; else = 0	0.72 (0.45); 0.71 (0.46)	0.72 (0.45)	0.76 (0.43)
High risk ^A (dummy variable)	Respondent indicated that home is located in a high-fire-risk neighbourhood; if Yes = 1; else = 0	0.06 (0.23); 0.04 (0.20)	0.05 (0.22)	0.1 (0.30)
Hispanic ^A (dummy variable)	Respondent indicated that they are Hispanic or Latino; if Yes = 1; else = 0	—	0.37 (0.48)	0.03 (0.18)
Age ^{B,D}	Respondent's age	58.3 (16.04); 47.9 (16.67)	54.4 (17.01)	58.1 (15.15)
Income ^{B,D}	Household annual income	\$39 084 (37 899); \$63 841 (47 697)	\$48 317 (43 394)	\$63 410 (47 786)
Education level ^{B,D}	Respondent's highest education level completed	13.9 (2.52); 14.7 (2.34)	14.2 (2.47)	14.7 (2.51)

^AThe mean proportional values are significantly different between FL minority and FL original at α level < 0.01.^BThe mean values are significantly different between FL minority and FL original at α level < 0.01.^CThe mean proportional values are significantly different between African-American and Hispanic at α level < 0.01.^DThe mean values are significantly different between African-American and Hispanic at α level < 0.01.

unobserved heterogeneity. The MNL model results (Table 6) for FL minority homeowners show that the *risk*, *loss* and *cost* variables are negative, statistically significant at the α level of 0.05, and consistent with rational economic decision-making. The *public* and *private* programs suggest that on average, respondents prefer the status quo (do nothing) alternative. However, Hispanics who perceived they lived in low- to moderate-risk areas prefer paying for new public wildfire protection programs.

Given that the basic MNL model cannot capture unobserved preference heterogeneity, we decided to use an RPL model to estimate homeowners' WTP for wildfire mitigation programs. Table 1 shows the RPL model results for FL minority homeowners. We tested the interactions between programs with income and Firewise variables, but they were statistically non-significant. Therefore, these interaction terms were not included in the final model. Results are available upon request. The *risk*, *loss* and *risk loss* variables were set as random parameters, following normal distribution for *risk* and *loss* and log-normal distribution for *risk loss*. The RPL model specification confirm that respondents made fully compensatory *risk-loss-cost* trade-offs as the estimated coefficients are negative and highly significant. Homeowners are basing their decisions on the relation with the risk associated with the potential loss and not necessarily on the cost of the choice. This means they are behaving according to economic theory. The Hispanic dummy and cost interaction has the correct negative sign and is

statistically significant at the 0.05 level. Because of interaction terms in the model, the marginal WTP of households who perceive they live in high-risk communities for public program is computed by adding the high risk public and public coefficients. Results suggest that FL minority homeowners perceived to be living in a high-risk community are willing to pay for 10-year public fire mitigation programs. We find that Hispanics do show a higher WTP than African-American households for both the public (\$1220 v. \$126) and private (\$826 v. \$181) wildfire risk-reduction programs. Homeowners perceived to be living in a low- to moderate-risk community prefer both the public and private wildfire risk-reduction programs. Using the public (private) program and cost coefficients, the marginal WTP of African-American homeowners living in a low- to moderate-risk communities for a 10-year project is \$3667 (\$2737) whereas Hispanic homeowners' marginal WTP is lower, \$2735 (\$2076). However, the WTP estimates are not statistically significantly different from each other. These results suggest that minority homeowners are willing to invest in wildfire risk-reduction programs, but Hispanics perceived to be living in low- to moderate-risk communities are willing to invest a lower amount than African-Americans. One possible reason for this result may be having a lower percentage of Hispanic (22% compared with 37% of African-American) households perceived to be living in low- to moderate-risk communities that have personal experience with wildfires.

Table 6. Multinomial logit model estimates of preference parameters for FL minority homeowners' wildfire hazard mitigation programs

The dependent variable is the alternative selected in the choice questions. Note: standard errors in parentheses. Statistical significance is indicated by **, <0.05

Variable	Multinomial logit model
Risk (%)	0.1829** (0.0781)
Loss (\$1000)	0.0083** (0.0042)
Cost (\$)	0.0003** (0.0001)
Hispanic DUMMY cost	0.0003 (0.0002)
Risk loss	0.1613 (0.1284)
Public program	0.041 (0.2050)
Public pro. $\times$ high risk	0.4014 (0.3811)
Private program	0.2807 (0.2101)
Private pro. $\times$ high risk	0.1227 (0.3896)
Hispanic dummy $\times$ public	0.4167** (0.1969)
Hispanic dummy $\times$ private	0.223 (0.2132)
N	319
McFadden R^2	0.018
Log-likelihood	1020.26

For the LC model, the clearest results were obtained for the two-class model. We tested several variables (e.g. Hispanic dummy, income, gender, education) in the membership class, but found that low-income (<\$38 000) household was statistically significant. In the two-class model (Table 2), only a constant, Personal experience with wildfires, and income were selected for the membership class. Results show that ~36% of respondents were classified in Class 1 (Less experience and lower-income group) and 64% in Class 2 (More experience and higher-income group). The Class 1 parameter estimate on risk is not significantly different than zero, whereas loss is significant, suggesting that respondents focus their attention on losses. Further, the negative sign and statistically significant coefficient for the public and private wildfire risk-reduction programs suggest that these respondents who perceive they are living in a low- to moderate-risk community are generally opposed to these type of mitigation programs and will need to be compensated to participate. This suggests that if respondents have never personally experienced a wildfire but are confronted with a high potential loss, they will be more inclined to pay to avoid that loss. Holmes *et al.* (2013, p. 242) explains this as 'Respondents without personal experience appeared to be confused about the risk and loss attributes, often exhibiting the wrong sign on parameter estimates associated with these attributes, and tended to anchor on the program labels'. For homeowners who have personal experience with wildfire, early studies (Gardner *et al.*

1987, Cortner *et al.* 1990) suggest that they do not believe that the wildfire will occur again, and thus have less incentive to pay for the programs as the probability of fire occurrence is much lower than before. Interestingly, homeowners who perceived they were living in a high-risk community seemed to prefer the status quo (do nothing) alternative instead of paying public program. This might be due to the fact that this group is composed of low-income households and do not have disposable income to pay for additional services. In contrast, respondents in Class 2 who perceived they were living in a low- to moderate-risk community had a positive WTP for reducing the risk of experiencing a financial loss from wildfires, and also had a higher propensity to support public and private mitigation programs, as suggested by the positive and statistically significant coefficients. Respondents who perceived they were living in a low- and moderate-risk area had a positive WTP of \$5622 (\$562 annually) and \$4759 (\$476 annually) for 10-year public and private wildfire risk reduction programs respectively.

Class 2 respondents who perceived they were living in a high-risk community were willing to participate in both program and pay an annual fee of \$176 for public and \$141 for private wildfire risk-reduction programs. A plausible explanation for these findings is that Class 2 respondents have higher household incomes and have personal experience with the effects of fires.

Comparing results (Table 2) with homeowners in the FL original study shows that, in general, both studies have the same significant coefficients. In both studies, Class 1 homeowners who perceived they live in a low- to moderate-risk community generally opposed these type of fire mitigation programs and will need to be compensated to participate. These results from this group may suggest a protest response by homeowners. For Class 2, homeowners who perceived they live in a low- to moderate-risk community are in favour of participating in both wildfire risk-reduction programs. Results from FL original data show that households in the two groups favour both wildfire risk-reduction programs. For high-risk communities and the public program, FL original households are willing to pay more than twice as much as minority households and three times as much for private program.

Table 7 shows the one-time WTP or willingness to accept (WTA) (negative values in table) estimates for a 10-year program for both datasets. Both models have the same classification, but the difference between them is that the FL original has a non-significant low-income-household variable. Results show the range of WTP expected. For FL minority homeowners perceiving they live in low- to moderate-risk communities and classified in the More experience and higher-income group, the one-time WTA estimate for both the public and private programs is higher than FL original homeowners' estimates. However, the large confidence interval suggests the mean WTP amounts are not significantly different across the two studies. For those homeowners in the Less experience and low-income group, the one-time WTA estimate is lower for both programs for FL minorities than FL original homeowners. However, they are not statistically significantly different across studies. FL minority homeowners who perceived they live in a high-risk community have a WTP for both groups whereas FL original homeowners have a WTP amount for the More experienced and high-income class.

Table 7. Latent class one-time WTP^A (WTA^B) per homeowner for a 10-year public and private wildfire risk reduction actions (2009 US dollars)
The Delta method was used to construct confidence intervals

	Homeowners			
	Mean WTP (WTA) low to moderate risk perception program		Mean WTP (WTA) high risk perception program	
	Public	Private	Public	Private
	(95% confidence interval)			
Class 1: FL minority homeowners	\$624	\$847	\$300	\$28
Less experience and low income	(\$1409, \$162)	(\$1767, \$73)	(\$1524, \$923)	(\$1119, \$1174)
Class 2: FL minority homeowners	\$5622	\$4759	\$1764	\$1409
More experience and higher income	(\$2771, \$8473)	(\$2287, \$7231)	(\$1881, \$5409)	(\$2307, \$5125)
Class 1: FL original homeowners ^C	\$938	\$992	\$309	\$1,228
Less experience and low income	(\$1526, \$350)	(\$1637, \$349)	(\$747, \$129)	(\$2299, \$157)
Class 2: FL original homeowners ^C	\$3386	\$2973	\$4766	\$4824
More experience and high income	(\$2612, \$4161)	(\$2256, \$3688)	(\$2855, \$6678)	(\$2883, \$6766)

^AWTP refers to willingness to pay.

^BWTA refers to willingness to accept.

^CWTP (WTA) estimates were converted from 2006 to 2009 dollars using the consumer price index (CPI) (Bureau of Labor Statistics 2016).

Conclusions

Both the RPL and the LC models used for analysis revealed some interesting findings. Using the RPL model, results suggest that minority homeowner are willing to invest in both public and private wildfire risk-reduction programs. In addition, we found that African-Americans living in low- to moderate-risk communities have higher WTP estimates for public programs than Hispanics. However, Hispanics living in high-risk communities have higher WTP than African-American households. For the LC model, FL minority respondents in the Less experience and low-income group in low- to moderate-risk areas prefer the do nothing or status quo alternative and respondents in the More experience and high-income group who perceived they were living in low- to moderate-risk areas and also in high-fire-risk areas expressed support for both the public and private wildfire mitigation programs. It appears that income and personal experience with wildfire are a critical factors when expressing support for wildfire protection programs. When comparing results with FL original household data in Holmes *et al.* (2013), we found similar results for the group classification. However, for the More experience and high-income group, households preferred both the public and private programs. Our results show that households in the Less experience and low-income group generally opposed these type of wildfire risk-reduction programs and prefer the status quo or need to be compensated to participate in either of the two programs. In addition, our choice experiment WTP estimates are similar to results (on an annual basis) reported in the literature.

Results suggest the highest priority for cost-sharing funds would go to homeowners with lower incomes and who have not experienced wildfires, and especially to cost-share private actions on their own land. Thus, our results would be informative to fire managers regarding targeting low-income minority households that live in low- to moderate-risk areas. They could also aid decisions on cost-sharing funds in terms of what types of actions and programs (private v. public) to cost-share. However, these results should only be used for Florida. Additional

research is needed to determine if preferences are the same for minorities residing in other states.

Conflicts of interest

The authors declare no conflicts of interest.

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References

- Adamowicz W, Louviere J, Swait J (1998) Introduction to attribute-based stated choice methods. Resource Valuation Branch Damage Assessment Center, NOAA, US Department of Commerce, Washington, DC, USA.
- Bowker JM, Lim SH, Cordell HK, Green GT, Rideout-Hanzak S, Johnson CY (2008) Wildland fire, risk, and recovery: results of a national survey with regional and racial perspectives. *Journal of Forestry* **106**(5), 268–276.
- Boxall PC, Adamowicz WL (2002) Understanding heterogeneous preferences in random utility models: a latent class approach. *Environmental and Resource Economics* **23**, 421–446. doi:10.1023/A:1021351721619
- Boxall PC, Adamowicz WL, Swait J, Williams M, Louviere J (1996) A comparison of stated preference methods for environmental valuation. *Journal of Ecological Economics*. **18**(3), 243–253. doi:10.1016/0921-8009(96)00039-0
- Bureau of Labor Statistics (2016) CPI inflation calculator. Available at <http://data.bls.gov/cgi-bin/cpicalc.pl> [Verified June 2016]
- Champ PA, Boyle K, Brown TC (2003) 'A Primer on Non-market Valuation.' (Kluwer Academic Publishers: Dordrecht, Netherlands)
- Cortner HJ, Gardner PD, Taylor JD (1990) Fire hazards at the urban–wildland interface: what the public expects. *Environmental Management* **14**(1), 57–62. doi:10.1007/BF02394019
- Fried JS, Winter GJ, Gilles JK (1999) Assessing the benefits of reducing fire risk in the wildland–urban interface: a contingent valuation approach. *International Journal of Wildland Fire* **9**(1), 9–20. doi:10.1071/WF99002

- Gaither CJ, Poudyal NC, Goodrick S, Bowker JM, Malone S, Gan J (2011) Wildland fire risk and social vulnerability in the south-eastern United States: an exploratory spatial data analysis approach. *Forest Policy and Economics* **13**(1), 24–36. doi:10.1016/J.FORPOL.2010.07.009
- Gardner PD, Cortner HJ, Widaman K (1987) The risk perceptions and policy response toward wildland fire hazards by urban home-owners. *Landscape and Urban Planning* **14**, 163–172. doi:10.1016/0169-2046(87)90021-1
- Holmes T, González-Cabán A, Loomis J, Sánchez JJ (2013) The role of personal experience on choice-based preferences for wildfire protection programs. *International Journal of Wildland Fire* **22**, 234–245. doi:10.1071/WF11182
- Kaval P, Loomis J, Seidl A (2007) Willingness-to-pay for prescribed fire in the Colorado (USA) wildland–urban interface. *Forest Policy and Economics* **9**, 928–937. doi:10.1016/J.FORPOL.2006.08.003
- Krupnick A, Alberini A, Cropper M, Simon N, O'Brien B, Goeree R, Heintzelman M (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. doi:10.1023/A:1014020027011
- Loomis J, duVair P (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. doi:10.2307/3146594
- Loomis J, González-Cabán A (2010) Forest Service use of non-market valuation in fire economics: past, present, and future. *Journal of Forestry* **108**(8), 389–396.
- Loomis JB, Hung LT, González-Cabán A (2009) Willingness to pay function for two fuel treatments to reduce wildfire acreage burned: a scope test and comparison of White and Hispanic households. *Forest Policy and Economics* **11**, 155–160. doi:10.1016/J.FORPOL.2008.10.006
- Meldrum JR, Champ PA, Warziniack T, Brenkert-Smith H, Barth CM, Falk LC (2014) Cost-shared wildfire risk mitigation in Log Hill Mesa, Colorado: survey evidence on participation and willingness to pay. *International Journal of Wildland Fire* **23**, 567–576. doi:10.1071/WF13130
- National Interagency Fire Center Wildland Fire Statistics (2014) Available at: http://www.nifc.gov/fireInfo/fireInfo_statistics.html [Verified June 2016]
- Radeloff VC, Hammer RB, Stewart SI, Fried JS, Holcom SS, McKeefry JF (2005) The wildland–urban interface in the United States. *Ecological Applications* **15**(3), 799–805. doi:10.1890/04-1413
- Scarpa R, Thiene M (2005) Destination choice models for rock climbing in the north-eastern Alps: a latent-class approach based on intensity of preferences. *Land Economics* **81**, 426–444. doi:10.3368/LE.81.3.426
- Smith VK, Desvousges W (1987) An empirical analysis of the economic value of risk changes. *Journal of Political Economy* **95**, 89–114. doi:10.1086/261443
- Train K (2009) 'Discrete Choice Methods with Simulation.' (Cambridge University Press: Cambridge, UK)
- US Census Bureau (2015) Quickfacts United States. Available at <http://www.census.gov/quickfacts/table/PST0415215/12> [Verified 1 July 2016]
- Walker S, Rideout D, Loomis J, Reich R (2007) Comparing the value of fuel treatment options in northern Colorado's urban and wildland–urban interface areas. *Forest Policy and Economics* **9**, 694–703. doi:10.1016/J.FORPOL.2006.06.001