

Are There Differences Between Minority Households Willingness-to-Pay for Wildfire Risk Reduction in Florida?¹

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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. Also to test for differences in response between the two groups. A random parameter logit and latent class models allowed us to determine if there is difference in wildfire mitigation program preferences and whether WTP is higher for public or private actions for wildfire risk reduction, and whether households with personal experience and perceiving living in higher risk areas have significantly higher WTP. We also compare FL minority homeowners' WTP values with general FL homeowners estimates. Results suggest that FL minority homeowners are willing to invest in public programs, with African-Americans WTP values twice as much as Hispanics. In addition, the highest priority for cost sharing funds would go to homeowners in areas who perceive their houses to be at high risk, and especially to cost share private actions on their own land. These results may help fire managers optimize allocation of scarce cost sharing funds for public vs private actions.

Keywords: choice experiment, firewise, latent class model, random parameter logit model, WUI

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Introduction

In the recent years, the United States has seen an increase and severity of wildland fires due to growing fire seasons, drier conditions, and accumulation of fuels. From 2000 to 2013, wildfires have affected over 37 million ha of forest and brush lands and federal fire protection agencies spent almost \$2 billion in suppression cost (National Interagency Fire Center Wildland Fire Statistics, 2014). Fire suppression expenditures for the first time in fiscal year 2015 exceeding 50% of USDA Forest Service (USFS) budget.

Wildland fires represent a threat to many communities nationwide. However, residential neighborhoods located in the wildland-urban interface (WUI- area where houses and undeveloped wildland vegetation meet)³ are prone to higher risk for loss of life and property. Increases in wildfire risks has led the USFS and state/local agencies to developed 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/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 nation on how much money households would pay to state and county agencies for funding wildfire reductions projects. For example, Loomis and González-Cabán (2010) surveyed households in California, Florida, and Montana and found that the mean willingness to pay (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 versus 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). More recently, Sánchez et al. (in review) used a choice experiment survey to determine CA homeowners' preferences and WTP for public and private wildfire mitigation programs. The authors found that CA homeowners that perceived to be living a high risk community, their WTP for a ten-year public program is \$1265 and \$1733 for a ten-year private program.

However, few studies have studied minority households WTP for fuel treatment projects. A study by Loomis et al. (2009) uses voter referendum survey question to compare across California, Florida, and Montana White and Hispanic

³ For a more complete definition of the WUI see Radeloff et al. (2005).

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 burn (mechanical) fuel treatment of 1 million White households is \$2,578 (\$3,376) per acre, while 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, less than 10% of survey participants were minorities (African-American and Hispanic). However, 28.9% of Florida population are from Hispanic and African-American descent (US Census, 2015). Therefore, their results are based on a partial segment of Florida population and results might not be representative of the entire state. This study expands Holmes et al. (2013) by focusing on the missing minority population. The significant increase in FL minority population from 2010 to 2015 highlights the importance of incorporating 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 whites population increased by 2.95% for the period, their percent of the total state population decreased from 57.9% to 55.3%⁴. 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 they respond differently to these programs. The research could also help fire managers to identify obstacles to the implementation of efficient fire mitigation programs and policies.

This study contributes to the literature by implementing a choice experiment to understand tradeoff minority's (African-American and Hispanic) households are willing to make between fire mitigation programs. We use the same choice experiment survey as Holmes et al. (2013) to estimate WTP for minority homeowner in Florida 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 involving prescribed burning, mechanical treatment and herbicide treatment of forests immediately surrounding their neighborhood; and (2) a Private Program that alters the vegetation surrounding the home such as reducing tall vegetation (more than 3 feet high) within 30 feet of their house⁵. A random parameter logit and latent class models allowed us to determine whether minorities WTP is higher for public or private actions for wildfire risk reduction, and whether households with personal

⁴ Data obtained from US Census (2015).

⁵ See www.firewise.org for more information on the Private Program.

experience and perceiving living in higher risk areas have significantly higher WTP. We will be able to assess residents' preferences for wildfire mitigation programs and to explore the heterogeneity of those preferences. In addition, analysis were done to ascertain if African American and Hispanic households respond different 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 models 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 individual's choices among alternatives (Train 2009). The choice experiment (CE) method has been widely used in marketing and transportation literature to analyze 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 an environmental good and/or services (Boxall et al. 1996).

The CE method provides more detailed information about public preference on environmental goods and services. The survey presented to respondents includes hypothetical scenarios describing specific issues along with description of attributes. Individuals are given choice sets, each of which usually consist of 3 alternatives (1 must be the status quo or opt-out option) to evaluate. 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/or services.

The CE method is based on the random utility theory and random utility theory uses the principle of utility maximization. Random utility models (RUM) describe discrete choices in utility maximizing frameworks. It is assumed that individuals select a good that provides 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}):

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

where U_{ni} is unobserved utility associated with individual n after selecting attribute 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 (iid). 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 as⁶:

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

where μ is a scale parameter that is typically set equal to one.⁷

The Random Parameter Logit (RPL) model often called Mixed Logit model is a generalization of the MNL model, and allows for random variation in preferences, unrestricted 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 .

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 via a continuous probability distribution for preference parameters. For more information on the MIXL model, readers are referred to Train (2009).

A latent class model (LCM) was used to capture preference heterogeneity for a finite number of heterogeneity classes (Boxall and Adamowicz 2002; Scarpa and Thiene 2005). 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 is:

$$(3) \quad \pi_{n|c}(i) = \frac{\exp(\mu_c \beta_c X_{ni})}{\sum_{k \in C} \exp(\mu_c \beta_c X_{nk})}$$

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

$$(4) \quad \pi_{nc} = \frac{\exp(\alpha \gamma_c Z_n)}{\sum_{c=1}^C \exp(\alpha \gamma_c Z_n)}$$

where α is a scale parameter (set equal to one), γ_c are specific class-related coefficients, and Z is a vector of individual's socio-demographics 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 equation 3 and 4:

⁶ This section relies on unpublished work provided José J. Sánchez.

⁷ 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.

$$(5) \quad \pi_n(i) = \sum_{c=1}^C \pi_{nc} \pi_{ni|c}$$

The parameter estimates are estimated by maximizing the log likelihood function:

$$(6) \quad \ln L = \sum_{j=1}^J \ln \left[\sum_{c=1}^C \pi_{nc} \left(\prod_{i=1}^I (\pi_{ni|c})^{y_{ni}} \right) \right]$$

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 estimates) of the attributes are measured by the parameter coefficient divided by the absolute value of cost coefficient.

$$(7) \quad MWTP = \frac{\beta_{program\ type}}{|\beta_{cost}|}$$

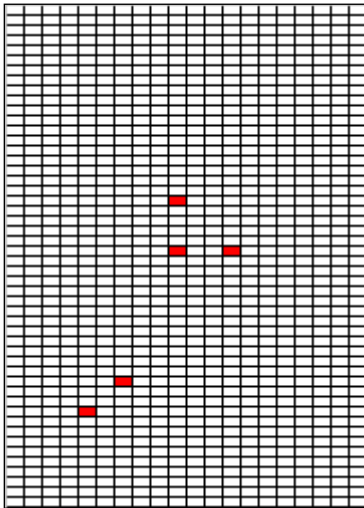
Using this formula and the wildfire hazard mitigation program and cost parameter estimates from tables 2 and 3, the one-time mean WTP for a ten year public and private programs can be derived (table 4).

Choice Experiment Survey Design

We used the same survey as Holmes et al. (2013) and was available both in English and Spanish. The survey began with several questions that asked respondents to answer questions about the vegetation around their home. These questions were followed by a characterization of what certain responses meant for the risk of wildfire in their neighborhood, and the risk of losing their house to a wildfire. Using Florida fire statistics, the current wildfire risk was characterized 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 1,000 cell square grid. The remaining white squares (figure 1) represent the risk of the house being undamaged. A risk ladder (figure 2) was presented to respondents as a way to convey the relative 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 the relative and absolute risks (Smith and Desvousges, 1987; Loomis and duVair, 1993; Krupnick et al., 2002).

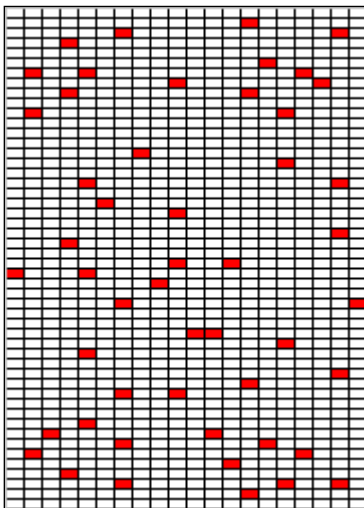
CHANCE GRIDS

(1) UPPER CHANCE GRID: Annual chance



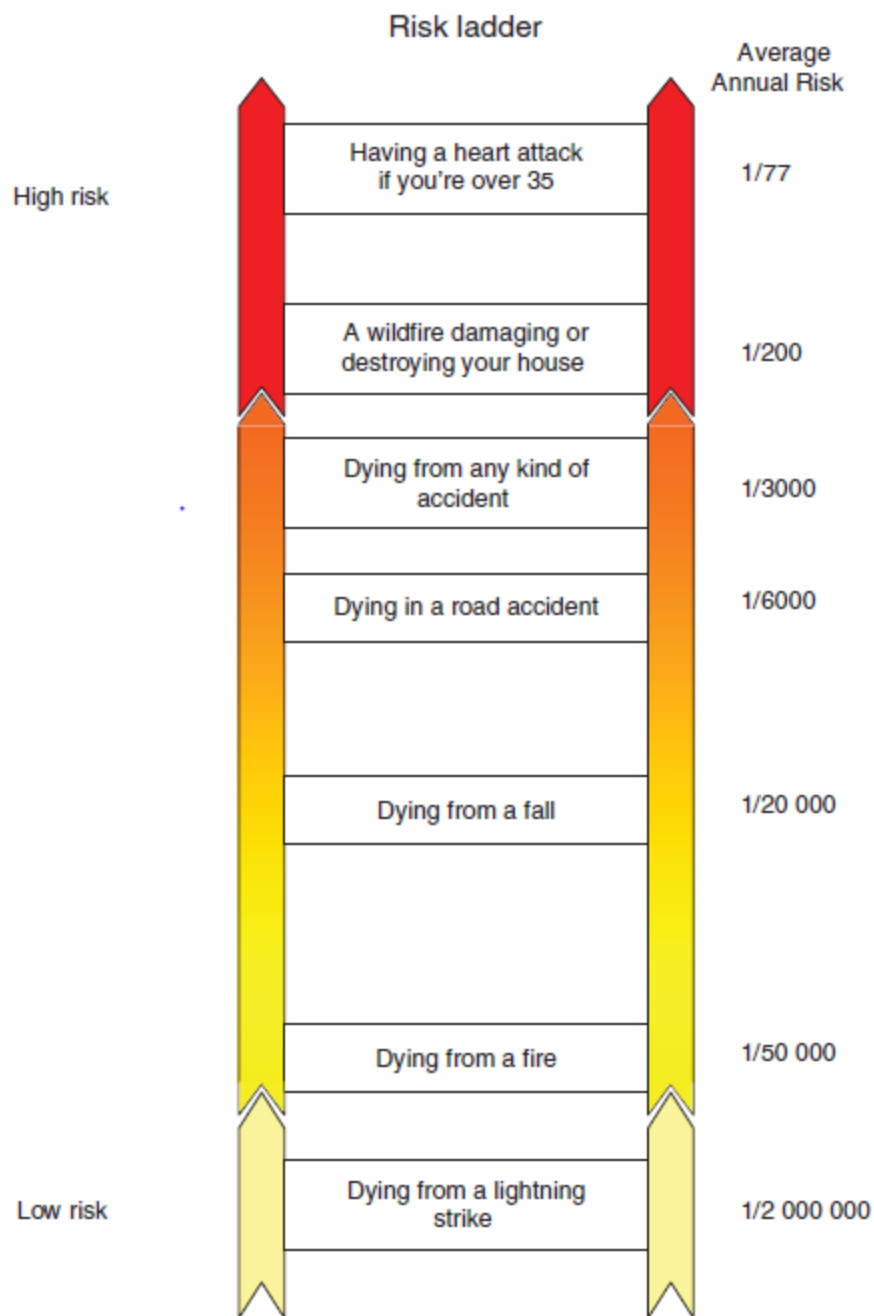
Another way to illustrate the Average Annual Chance of a wildfire damaging your house is shown in the diagram to the left. The “chance grid” shows a neighborhood with 1000 houses, and each square represents one house. The white squares are houses that have not been damaged or destroyed by wildfire, and 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 1. Risk grids to convey relevant degree of wildfire risk to homeowner survey participants (used with permission from Holmes et al. 2013).



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 ~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 ~1 in 200 homeowners) is quite a bit larger than the risk of dying from a fire (this will happen to ~1 in 50 000 people).

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

The survey implemented a full factorial randomized experiment design (see Holmes et al. 2013) to construct the choice sets. The choice experiment used four attributes of the survey: (1) *risk (%)* or chance (out of 1,000) of your house being damaged by wildfires in the next 10 years; this *risk* varied over five levels, from 1-5%, where 5% was the baseline risk respondents were told was associated with no new investments in wildfire protection programs;⁸ (2) monetary damage (*loss*) to property from the wildfire; the *loss* varied over 10 levels that ranged from \$10,000-\$100,000; (3) expected 10 year loss = chance x damage; attribute #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 ten-year program that varied over 10 levels from \$25-\$1,500 for the Public Program and 9 levels from \$50-\$1,500 for the Private Program.

An example of a choice question used in the questionnaire is shown in figure 3. 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 respondent’s house, monetary amount of damage, expected loss (chance times damage), and a one-time cost for implementing the selected ten-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 to each respondent, inducing the panel nature of the response data.

	Alternative 1	Alternative 2	Alternative 3
	Public Fire Prevention	Private Fire Prevention	Do nothing additional
Chance of your house being damaged in next 10 years	10 in 1,000 (1%)	25 in 1,000 (2.5%)	50 in 1,000 (5%)
Damage to property	\$10,000	\$50,000	\$100,000
Expected 10 year loss = Chance x damage	\$100 during 10 years	\$1,250 during 10 years	\$5,000 during 10 years
One-time cost to you for the ten-year program	\$100	\$500	\$0
I would choose: Please check one box	☐	☐	☐

Figure 3. Example of the Choice Set

⁸ We use *italics* to denote variables used in the empirical analysis.

Data

A stratified random sample of households was drawn from the population of African-American and Hispanics 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 dialing, 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 Hispanic 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 1 shows the descriptive statistics for variables in our survey sample and general FL homeowners' data in Holmes et al. (2013). We also test if there was a difference between the variables for both states. The sample consisted of 63% being African-American and 37% Hispanic. The stratified sample included a substantial proportion of respondents with personal experience of the effect of wildfire (31%). 12% of respondents reported health effect 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 that perceive to be living in a high risk community are low-income households (79% have less than \$38,000 annual household income). Approximately 72% (*firewise*) of respondents indicated that they previously improved the defensible space on their property (trim lower branches on tree = 58%, removed vines from tress = 50%, remove branches over home = 53%, remove trees and flammable plants = 36%).

In this paper we focus on the RPL model to compare African-American and Hispanic homeowners fire mitigation program preferences and LC model to compare

FL minority homeowners WTP estimates with general FL homeowner data (Holmes et al., 2013).

Table 1. Variables descriptive statistics

Variable	Description	Mean (std. dev.)	Mean (std. dev.) ⁹
health (dummy variable)	Health of respondent or family member suffered from breathing smoke from wildfire; if Yes = 1; else = 0	0.12 (0.33)	0.15 (0.35)
Travel ^a (dummy variable)	Household travel plans changed because of a wildfire; if Yes = 1; else = 0	0.27 (0.44)	0.35 (0.48)
personal experience ^a (dummy variable)	If either (health = 1 or travel = 1) = 1; else = 0	0.31 (0.46)	0.43 (0.50)
fire wise (dummy variable)	Household conducted at least one activity to reduce wildfire risk; if Yes = 1; else = 0	0.72 (0.45)	0.76 (0.43)
high risk ^a (dummy variable)	Respondent indicated that home is located in a high fire risk neighborhood; if Yes = 1; else = 0	0.05 (0.22)	0.10 (0.30)
Hispanic ^a (dummy variable)	Respondent indicated that they are Hispanic or Latino; if Yes = 1; else = 0	0.37 (0.48)	0.02 (0.13)
Age ^a	Respondent's age	54.4 (17.01)	58.1 (15.15)
Income ^b	Household annual income	48,317 (43394)	63,410 (47786)
Education level ^b	Respondent's highest education level completed	14.2 (2.47)	14.7 (2.51)

a. The mean proportional values are significantly different between FL and CA at alpha level < .01.

b. The mean values are significantly different between FL and CA at alpha level < .01.

Table 2 show the RPL model results for FL minority homeowners. The cost coefficient has the expected negative sign and is highly significant. Also, the

⁹ General FL homeowners' data from Holmes et al. (2013).

Hispanic dummy variable and cost coefficient interaction is statistically significant at the .10 level. Results suggest that FL minority homeowners perceived to be living in a high risk community are opposed to any type of fire mitigation programs and prefer the status quo (do nothing) alternative. However, homeowners perceived to be living in a low to moderate risk community prefer the public program. Using the public program and cost coefficient, the African-American homeowners marginal WTP is \$1,376 while Hispanic homeowners marginal WTP is lower (\$639). However, the WTP estimates are not statistically significantly different from each other. These results suggest that minority homeowner are willing to invest in fire mitigation programs; however, Hispanics are willing to invest only half the amount of African-Americans.

Table 2. Random parameter logit model estimates of preference parameters for wildfire hazard mitigation programs with random parameters estimated for risk and loss variables (The dependent variable is the alternative selected in the choice questions).

Variable	Random Parameter Logit Model	
	mean	std. dev.
<i>risk (%)</i>	-0.0702 (0.6566)	0.6926*** (0.0973)
<i>loss (\$1,000)</i>	0.0034 (0.0038)	0.0426*** (0.0052)
<i>cost (\$)</i>	-0.0004*** (0.0002)	--
<i>Hispanic Dummy*cost</i>	-0.0005* (0.0003)	--
<i>public program</i>	0.6094*** (0.2350)	--
<i>public pro.*high risk</i>	-0.6122 (0.5963)	--
<i>private program</i>	0.2219 (0.2412)	--
<i>private pro.*high risk</i>	-0.3342 (0.6939)	--
<i>Hispanic Dummy*public</i>	0.4947 (0.3259)	--
<i>Hispanic Dummy*private</i>	0.1838 (0.3406)	--
N	319	--
McFadden R ²	0.1334	--
Log Likelihood	-911.16	

Note: standard errors in parentheses. * indicates significance at the 0.10 level, *** indicates significance at the 0.01 level.

For the LC model, the clearest results were obtained for the 2-class model. In the two-class model (table 3), results show that about 36% of respondents were classified in Class 1 (Less Experience group) and 64% in Class 2 (More Experience

group). The Class 1 parameter estimate on risk is not significantly different than zero, while loss is significant, suggesting that respondents focus their attention on losses. Further, the negative sign and statistically significant coefficient for the public and private mitigation programs suggest that these respondents who perceive to be 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. Surprisingly, those homeowners that perceived to be living in a high risk community, prefer the status quo (do nothing) alternative. In contrast, respondents in Class 2 who perceived to be living in a low to moderate risk communities have a positive WTP for reducing the risk of experiencing a financial loss from wildfires. And also have a higher propensity to support public and private mitigation programs as suggested by the positive and statistically significant coefficients. Respondents living in a low and moderate risk area have a positive WTP for 10-year public (\$5,610) and private (\$4,757) programs.

Surprisingly, Class 2 respondents that perceive to be living in a high risk community have a negative WTP sign for both the public and private program; implying they would have to be compensated (willingness-to-accept - WTA) to participate in the public (\$405 annually) and private (\$359 annually) programs. A plausible explanation for these findings is that the majority of respondents that perceive to be living in a high risk community are low-income households (79% have less than \$38,000 annual household income). This means these households do not have sufficient disposable income to cover the additional expenses for fire mitigation programs. In addition, 79% of households perceived to be living in a high risk community indicated that they have wildfire insurance protection and 63% had previously improved the defensible space on their property. Therefore, they might be under the impression that no additional protection is needed.

Table 3. Latent class model estimates of homeowner preference parameters for wildfire hazard mitigation programs among survey respondents

Variable	Two-class model		Two-class model (Holmes et al., 2013) ¹⁰	
	Class 1	Class 2	Class 1	Class 2
<i>risk (%)</i>	0.0994 (0.1070)	-0.1168*** (0.0428)	0.0003 (0.0877)	-0.1135*** (0.0263)
<i>loss (\$1,000)</i>	0.0149** (0.0067)	-0.0052** (0.0022)	-0.0087* (0.0045)	-0.0041*** (0.0013)
<i>cost (\$)</i>	-0.0016*** (0.0005)	-0.0005*** (0.0001)	-0.0027*** (0.3687)	-0.0007*** (0.0001)
<i>public pro.</i>	-1.042** (0.4352)	2.5774*** (0.3042)	-2.401*** (0.3687)	2.1532*** (0.1682)
<i>public pro. *hi risk</i>	0.4161 (1.0517)	-1.8601** (0.8304)	1.6074*** (0.4304)	0.8749 (0.5535)
<i>private program</i>	-1.4469*** (0.4743)	2.1853*** (0.3073)	-2.5368*** (0.3998)	1.8902*** (0.1708)
<i>private pro. *hi risk</i>	1.424 (0.9354)	-1.6508* (0.8714)	-0.601 (1.0937)	1.1748** (0.561)
Covariates explaining latent class membership ^a				
<i>constant</i>	-0.4100*** (0.1511)	--	-0.2594*** (0.0958)	
<i>personal experience</i>	-0.5426* (0.2823)	--	-0.5871*** (0.1457)	
average class probability	0.36	0.64	0.38	0.62
n	319		922	
McFadden R ²	0.227		0.243	

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.

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

Comparing results (table 3) with general FL homeowners (Holmes et al., 2013) shows that in general both studies have the same significant coefficients. In both studies, Class 1 homeowners that perceived to be living in a low to moderate risk community generally opposed these type of fire mitigation programs and will need to be compensated to participate. For Class 2, homeowners that perceived to be living in a low to moderate risk communities are in favor of participating in both fire mitigation programs. However, there are differences when comparing households that perceive to be living in a high risk community. Results from general FL data (Holmes et al., 2013) shows that households from both classes prefer either the status quo or one of the fire mitigation programs. This is not the case for minority households in Class 2. These households have negative coefficients meaning that they generally opposed to these type of fire mitigation programs and will need to be compensated to participate.

¹⁰ Data used from Holmes et al. (2013). Model estimated without public program and defensible space interactions to make comparisons.

Table 4 shows the one-time WTP or WTA (negative values in table) estimates for a 10-year program for both data sets. For FL minority homeowners in the Less Experience group, the one-time WTA estimate for both the public and private programs are always lower than general FL homeowners estimates. However, the large confidence interval suggest the mean WTP amounts are not significantly different across the two studies. For those homeowners in the more experience group, the one-time WTP estimate are higher for both programs for FL minorities than general FL homeowners. However, they are not statistically significantly different across studies. FL minority homeowners that perceived to be living in a high risk community have a WTA while general FL homeowners have a WTP amount.

Table 4. One-time WTP/WTa per homeowner for a ten year Public and Private wildfire risk reduction actions (2009 Dollars).

	Homeowners			
	Mean WTP/WTa Low to Moderate Risk Perception Program		Mean WTP/WTa High Risk Perception Program	
	Public	Private	Public	Private
	----- (95% Confidence Interval ^b) -----			
FL minority homeowners Less Experience	-\$640 (-\$1419, \$139)	-\$889 (-\$1815, \$37)	- -	- -
FL minority homeowners More Experience	\$5610 (\$2764, \$8456)	\$4757 (\$2288, \$7226)	-\$4049 (-\$8078, -\$20)	-\$3593 (-\$7699, \$512)
FL Homeowners ^a Less Experience	-\$942 (-\$1528, -\$354)	-\$995 (-\$1637, -\$352)	\$630 (\$195, \$1065)	- -
FL Homeowners ^a More Experience	\$3387 (\$2615, \$4160)	\$2973 (\$2258, \$3688)	- -	\$1848 (\$64, \$3633)

a. WTP/WTa estimates were converted from 2006 to 2009 dollars using CPI (Bureau of Labor Statistics, 2016).

b. Delta method was used to construct confidence intervals.

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 only in a public wildfire mitigation program. In addition, we found that African-American have a higher WTP estimates for public program than Hispanics. For the LC model, respondents in the Less Experience group with exposure to wildfires preferred the do nothing alternative and respondents in the More Experience group with exposure to wildfires that perceived to be living in low to medium fire

risk expressed supported for both the public and private wildfire protection programs. However, we were surprised to find that respondents that subjectively rated living in a high risk area would prefer the do nothing alternative. It appears that income is a critical factor when deciding to support wildfire protection programs. When comparing results with general FL household data in Holmes et al. (2013), we found similar results for the Less Experience group. However, for the More Experience group, different household preferences are seen. General FL households (Holmes et al., 2013) prefer the private program, but status quo instead of a public program. Our results show that households in the More Experience group generally opposed to these type of fire mitigation programs and need to be compensated to participate in either of the two programs.

Results suggest the highest priority for cost sharing funds would go to homeowners in areas who perceive their houses to be at high risk, 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 a high risk area. It could also aid decisions on cost sharing funds in terms of what types of actions/programs (private vs public) to cost share.

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