A Comparison of Wildland Urban Interface Households WTP for Wildfire Risk Reduction Programs in California and Florida[1]

José J. Sánchez[2], John Loomis[3], Armando González-Cabán[2], Tom Holmes[4]

Abstract

Using the same choice experiment surveys and same specification of mixed logit models are used in California (CA) and Florida (FL) to compare homeowners willingness to pay (WTP) for two types of fuel reduction programs. Comparing the WTP of homeowners in CA and FL for private and public wildfire risk reduction show that WTP for the private actions among households who perceive low to moderate wildfire risk is quite low, and probably lower than what their cost share would be for making significant wildfire risk reductions on their property and to their residence. However, these same individuals would pay substantially more for public programs to reduce wildfire risk in their neighborhoods and common/public lands around their neighborhoods. The results also 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.

Keywords: benefit transfer, fuel reduction programs, mail survey, mixed logit model, willingness to pay.

[1] An abbreviated version of this paper was presented at the Fifth International Symposium on Fire Economics, Planning, and Policy: Wildfires and Ecosystem Services, November 14-18, 2016, Tegucigalpa, Honduras.

[2] Research Statistician and Research Economist respectively, USDA Forest Service, Pacific Southwest Research Station, Riverside, CA 92507; email: jsanchez@fs.fed.us

[3] Professor, Department of Agricultural and Resource Economics, Colorado State University, Fort Collins, CO 80523;

[4] Research Forest Economist, USDA Forest Service, Southern Research Station, Research Triangle Park, NC 27701

Introduction

Over the last two decades, there has been a large movement of the United States' population into Wildland Urban Interface (WUI) areas. This is particularly evident in California (CA) and Florida (FL), two of the most populous states in the USA. These states also have millions of residents living in WUI areas with high or in the case of CA, extreme risk of severe wildfires. To reduce wildfire risk, the USDA Forest Service (USFS), State Forestry agencies and local counties have cost shared with private homeowners and communities wildfire risk reduction actions. Further, these agencies have directly paid for fuel reduction efforts on public and private lands surrounding many of these communities. However, these are costly programs to private homeowners and federal/state/county fire management agencies. To induce participation, cost share programs have been provided. However, there are very limited federal funds and it is important for the USFS to know what geographic areas have the highest economic values for reducing wildfire risk and the relative values of wildfire risk reduction actions to homeowners. In particular, the cost sharing only reduces the cost to the landowner, and if their WTP falls below their cost share, they will not engage in private actions to reduce wildfire risk on their properties or support homeowner associations' actions.

Thus, the purpose of this paper is to derive and compare the WTP of homeowners in CA and FL for private and public wildfire risk reduction. We estimate homeowner willingness to pay (WTP) to reduce the risk of forest fire in and around where people live in the two states. Two fire risk reduction programs are valued: (1) a Public Program that would be carried out by public forest managers involving prescribed burning, mechanical treatment and herbicide treatment of forests immediately surrounding their neighborhood; and (2) paying for 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 house.

We choose CA and FL because there are active fuel reduction programs in both states. While the forest type may be different, the experience of large and repeated wildfires in these two states suggests that residents living there are familiar with wildfire risk from forests. We valued the same two programs with the same choice experiment survey using the same survey mode in both CA and FL.

The paper proceeds as follows: first we review the literature, followed by presentation of the choice experiment survey design and survey mode. Then the data is described, the mixed logit specification discussed, and then the econometric results are presented. These results are followed by the WTP estimates in FL using two different approaches for inflation adjustment to the date of the CA survey.

Literature Review

There have been two sets of CVM surveys of what households would pay for state and county wildfire risk reduction projects in CA, FL and Montana (MT) (Loomis and González-Cabán, 2010) and in Colorado (Walker et al., 2007). The wildfire risk reduction projects all involved mechanically thinning and prescribed burning of the forests in the county where the households reside. Thus, there is some similarity of the programs valued in those studies to our Public Program as both involved prescribed burning and mechanically reducing forest vegetation. The CVM surveys used a voter referendum format where households voted in favor or against paying their household's share of a county fuel reduction program. The exact form of the payment (e.g., sales tax, property tax, etc.) was purposely not made explicit to reduce protest responses. Loomis and González-Cabán's (2010) CVM studies reported mean WTP per household for prescribed burning for CA, FL, and MT at $460, $392, and $323 respectively. The mean WTP per household for the mechanical fuel reduction method in CA, FL and MT was $510, $239, and $189 respectively. Of particular interest for our case study is the comparison of the CA and FL. These values per household are relatively similar for prescribed burning in the two states, but different by a factor of two for mechanical fuel reduction. All three studies reported in Loomis and González-Cabán (2010) specified a public program that would reduce the number of acres burned and the number of houses that would be destroyed.

However, none of these three past CVM studies explicitly stated the amount of risk to a person's house from wildfires, and the monetary amount of damages likely to their house from wildfires as the choice experiment study we are reporting on in this paper. In this new study we specify to the respondent the monetary damage, which ranged from partial loss to complete loss of their home. In addition, we computed for the respondents their expected damages (risk times damages) to property. Our new study in CA and FL also includes a separate WTP estimate for a Private Program around the individual person's house. Despite the difficulty with risk communication (see Smith and Desvousges, 1987) we feel that discussing risk to their homes may be a more meaningful way to communicate the potential effects of forest fires on WUI homeowners than just acres burned in the county or state, and houses completely destroyed. Thus, focusing on risk of fires to their house and damages might improve the WTP estimates for wildfire mitigation programs in CA and FL.

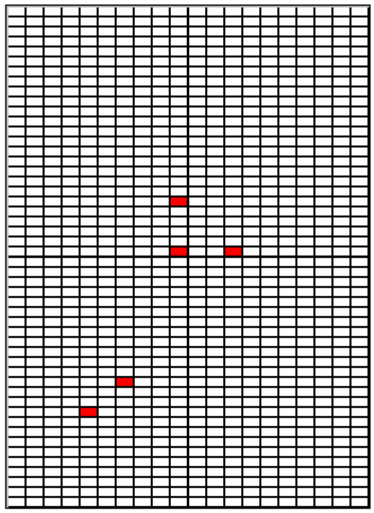
Choice Experiment Survey Design

The survey began with several questions that asked the respondent 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 fire statistics from the respective states, the current wildfire risk was characterized using a risk ladder and risk chance grid. The chance grid illustrated the chance of a home being damaged by a wildfire, represented as the number of red squares on a 1,000 cell square grid. The risk of the house being undamaged was represented by the remaining white squares (fig. 1). 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), a risk ladder (fig. 2) was presented to respondents. 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; Holmes et al., 2013).

Fig 1 Risk grids to convey relevant degree of wildfire risk to homeowner survey participants.

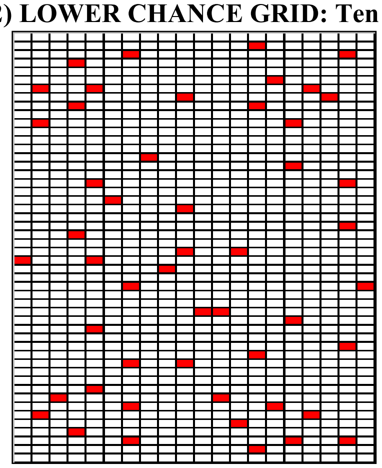
CHANCE GRIDS

(1) UPPER CHANCE GRID: Annual chance



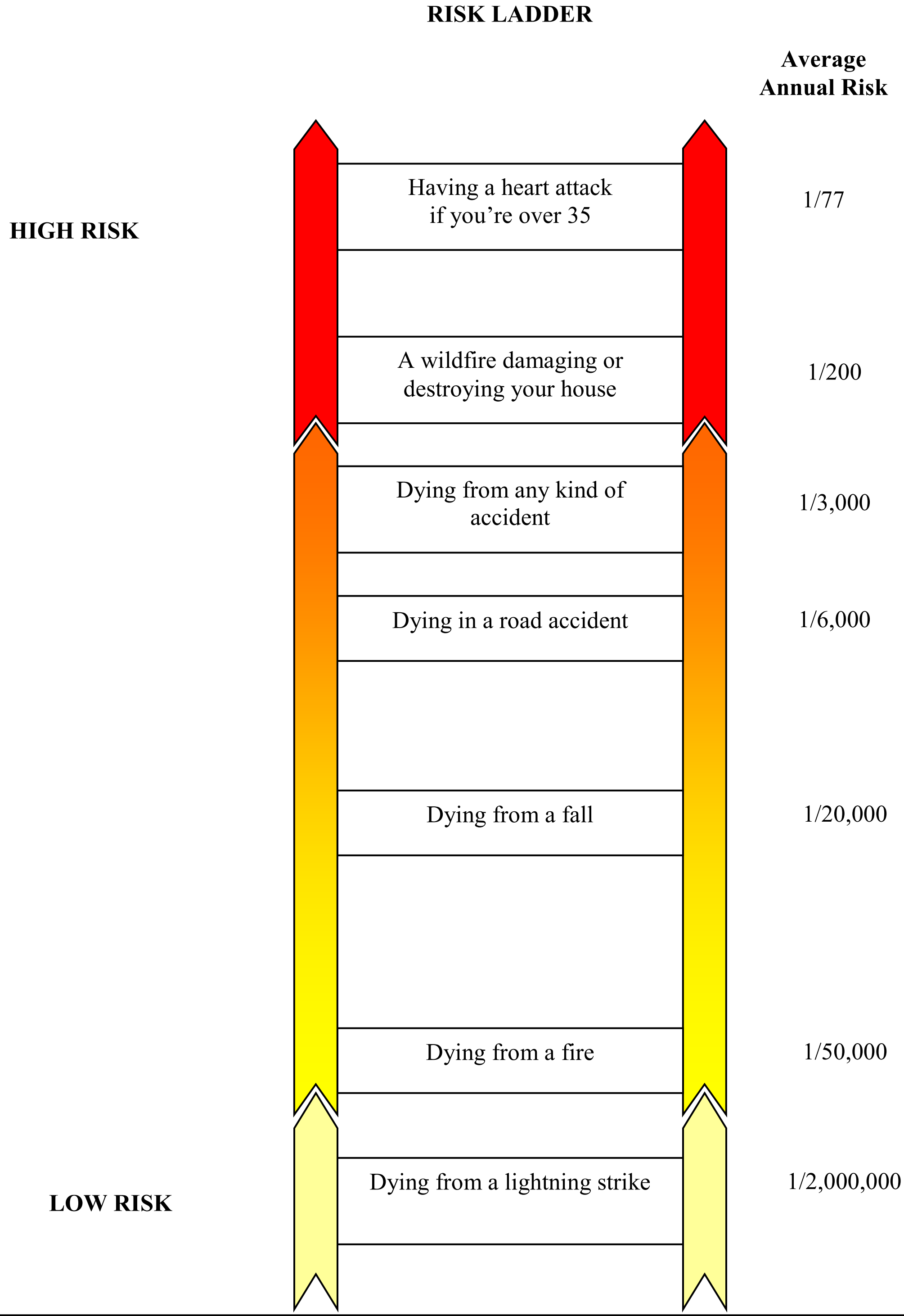
Another way to illustrate the Average Annual Chance of a wildfire damaging your house is shown in the diagram to the left. The "chance grid" shows a neighborhood with 1000 houses, and each square represents one house. The white squares are houses that have not been damaged or destroyed by wildfire, and 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.

Fig 2 Risk ladder used to illustrate to survey participants the risk of wildfires relative to other, ordinary daily events.



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).

The FL survey implemented a full factorial randomized experiment design to construct the choice sets. See Holmes et al. (2013) for information on constructing the full factorial design. For the CA survey, we used an efficient fractional factorial design using Ngene software (Rose et al., 2014). Both surveys used the same four attributes of the choice experiment: (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% to 5%, where 5% was the baseline risk respondents were told was associated with no new investments in wildfire protection programs;[5] (2) monetary damage (*loss*) to property from the wildfire; the dollar amounts of the *loss* varied over 10 levels that ranged from $10,000 to $100,000; (3) expected ten 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; the *cost* of the programs varied over 10 levels from $25 to $1,500 for the Public Program and 9 levels from $50 to $1,500 for the Private Program.

Three choice sets, each with three alternative programs, were presented to respondents: (1) Public Fire Prevention in the forests around their neighborhood; (2) Private Fire Prevention; and (3) Do nothing additional. Each alternative program included chance of damage to respondent's house, monetary amount of damage, expected ten year loss, and a one-time cost for implementing the selected ten year program. Fig. 3 present an example of one of the three choice sets presented in the survey.

[5] We use *italics* to denote variables used in the empirical analysis.

Fig 3 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 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	□	□	□

Data

Stratified sampling of households in the two states was used with more homeowners chosen from counties rated as having high or extreme wildfire danger than from those with medium or low wildfire risk. Data were collected using random digit dialing of households followed by a mail survey sent to single family homeowners providing an address (we did not survey renters). We obtained 922 usable surveys out of 2,000 mailed in FL for a 46% response rate. In CA, from 1,449 deliverable surveys we obtained 429 usable surveys for a 30% response rate.

Table 1 compares the descriptive statistics about homeowners in CA and FL. The survey responses indicate that when it comes to experience with wildfires the homeowners in FL and CA are quite similar. Homeowners were similar in their responses to whether they or a family member had ever experienced wildfire health effects from breathing wildfire smoke **or** had to change their travel plans due to wildfires. The two responses were merged into a new variable (*Personal Experience*) and used to capture the influence of respondent experience with actual wildfires. In particular, forty-three percent (43%) in FL and 47% in CA had experienced health effects or changes in travel plans due to wildfire. After reading the descriptions of high, medium and low fire risks landscapes around homes and neighborhoods respondents were asked whether they perceived their house and neighborhood to be at high, medium or low risk. Those that thought they were at high wildfire risk were labeled *high risk* as our measure of a risk perception variable. Approximately a tenth of homeowners perceived they were in a high risk area (10% in FL and 7% in CA).

Thus, in terms of wildfire experience and risk perception, FL and CA homeowners are quite similar. Using a proportional test, we found that there was a significant proportional mean difference (alpha level < .01) between CA and FL for the *high risk* variable, but no significant difference for the *personal experience* variable.

Table 1 also shows the three demographic variables we collected. To test whether there were statistically significant differences between CA and FL age, education and income, we first tested whether the variances were equal for these variables between the two states. Specifically, Bartlett's tests were performed independently to test the equal variance assumption for *age*, *income*, and *education level* variables. Results suggest that the variance is different between FL and CA for the *age* and *education level* variables. Therefore, Welch's two sample t-tests, which assumes unequal variance, was performed to test the mean difference for *age* and *education level* and a t-test was perform for *income* variable. Results show that the mean values for *age*, *income*, and *education level* variables are significantly difference between the two states. The largest difference between FL and CA homeowners is for age, with FL homeowners being younger than CA homeowners by seven years. Therefore we test for whether an age interaction coefficient was statistically significant and resulted in economically meaningful differences in WTP. In addition, we conducted a likelihood ratio test to test whether the two datasets should be pooled or have two separate models. Results suggest that we should have two models, one for each state.

Table 1. Descriptive statistics of homeowners in Florida (FL) and California (CA)

Variable	Description	Mean (std. dev.) FL	Mean (std. dev.) CA
personal experience (dummy variable)	If either (health related = 1 or travel disruption= 1); else = 0	0.43 (.50)	0.47 (0.50)
high risk[a] (dummy variable)	Respondent indicated that home is located in a high fire risk neighborhood; if Yes = 1; else = 0	0.10 (0.30)	0.07 (0.26)
Age[b]	Respondent's age	58 (15.15)	65 (13.10)
Income[b]	Household annual income	$87,178[c] (50,283)	$83,695 (51,107)
Education level[b]	Respondent's highest education level completed	14.66 (2.51)	15.66 (2.78)

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.
c. Adjusted to 2014.

Econometric Models of Choice Experiment Responses

The standard multinomial logit model (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. Random utility models are based on the notion that utility is the sum of systematic (V_{nj}) and random (ε_{nj}) components:

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

where x_{jnk} 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_{jn} is an error term that reflects factors unobservable to the researcher and hence is treated as a stochastic variable. 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:

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

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

The Mixed Logit (MIXL) 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). The independence of irrelevant alternatives assumption, which is imposed to estimate the MNL model, may be relaxed by introducing additional stochastic components to the utility function through β_n. These components allow the preference parameters for the x_{jnk} explanatory variables to directly incorporate heterogeneity:

$$\beta_{nk} = \beta_k + \Gamma\upsilon_{nk} \qquad (3)$$

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

[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.

assumed to be normally distributed across respondents and correlation of preferences across attributes is permitted.

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

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

where

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

The function f(β|θ) can be simulated using random draws from various functional forms (Train 2009). We use Halton draws from the normal distribution to estimate Γ for the random parameters in the MIXL model. The MIXL model captures heterogeneity via a continuous probability distribution for preference parameters.

Because the FL data was collected in 2006 and the CA data was collected in 2014, we need to scale up FL 2006 WTP estimates to 2014 (Eiswerth and Shaw, 1997). Eiswerth and Shaw indicate they see “no flaw” in updating the WTP estimates by the Consumer Price Index (CPI) for use oriented values (Eiswerth and Shaw, 1997: 2382). Since our study is of homeowners WTP to reduce the risk of damage to their home from wildfire, we would characterize this as a use value, and apply the CPI (US Census Bureau, 2015) to the estimated 2006 WTP values. In this paper we also offer a different way to use the CPI: update the “bid” or cost amounts households are asked to pay in the choice experiment by the CPI and re-estimate the model. That is, if we were to re-run the choice experiment survey in 2014 in FL, we would have set a bid vector and the monetary amount of the house loss that was higher than what the pre-tests suggested was appropriate in 2006. Given the sizeable non-linearity in a mixed logit model we want to test whether these two approaches (i.e., updating the model estimates of the WTP values versus updating the bid and house loss vectors) will yield the same inflation adjusted WTP estimates. Thus, we compare the resulting two approaches to update WTP for inflation. A priori given the non-linearity in the MIXL model, it is not clear whether these two approaches would yield similar estimates in WTP.

Econometric Results

Initially MNL, MIXL were estimated in CA and FL. The MIXL model was the most robust in terms of statistically significant coefficients with signs consistent with economic theory. In addition, the MIXL model specification greatly improved the pseudo-R^2 values relative to the MNL model. Therefore, in the remainder of the paper we focus on the results from MIXL model. Part of the improvement in goodness of fit is due to the statistical significance of the standard deviations of the variables. These standard deviations have an economically meaningful and management relevant interpretation: there is a great deal of heterogeneity of preferences or attitudes toward what the variable represents. For example, significant standard deviations on risk might signal that some people are more risk averse than others, and some might even be risk neutral, focusing primarily on the expected value of the risk of loss and hence more tolerant of living in areas where there is a risk of forest fires. From a statistical standpoint controlling for heterogeneity in preferences helps to ensure an unbiased coefficient on the main attribute variable itself.

Identical specifications of the MIXL models were estimated in CA and FL. The models included two Alternative Specific Constants (ASC); one for the Public Program (*public program)* and one for the Private Program (*private program*). Because a respondent's preference may vary by whether the respondent perceives they live in an area of high wildfire risk or not, we created an interaction term relating the perception of living in high risk wildfire areas (*high risk)* with the Public wildfire Program ASC (*public pro*high risk)* and Private Program (*private pro*high risk*). In both CA and FL, coefficients on both of these interaction variables were positive and statistically significant suggesting the importance of risk perception in the choice to pay for the Public and Private Programs (see Table 2 for FL and Table 3 for CA). The positive signs on the two risk perception interaction terms will result in higher WTP for both programs by homeowners who perceive they live in areas at high risk of wildfire.

Table 2. Florida Mixed logit (MIXL) 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)[7].

Variable	Mixed logit Model Original Cost Bids		Mixed logit Model Adjusted Cost Bids	
	(mean)	(std. dev.)	(mean)	(std. dev.)
risk (%)	0.1180*	0.8760***	0.1152*	0.8694***
	(0.0604)	(0.0657)	(0.0601)	(0.0656)
risk personal exp.*	-0.1801**	0.0035	-0.1789**	0.007
	(0.0830)	(0.3058)	(0.0825)	(0.3109)
loss ($1,000)	0.0072**	0.0424***	0.0061**	0.0362***
	(0.0030)	(0.0033)	(0.0025)	(0.0028)

[7] Both analyses used the same fix seed.

loss personal exp.*	-0.0123***	0.0022	-0.012***	0.0025
	(0.0040)	(0.0130)	(0.0039)	(0.0133)
cost ($)	-0.0011***		-0.0009***	
	(0.0001)		(0.0001)	
public program	0.7853***		0.7827***	
	(0.1224)		(0.1223)	
*public pro.*high risk*	1.1016***		1.0968***	
	(0.3087)		(0.3083)	
private program	0.4038***		0.3978***	
	(0.1257)		(0.1255)	
*private pro.*high risk*	1.4749***		1.4738***	
	(0.3127)		(0.3124)	
N	922	--	922	--
McFadden R^2	0.1590	--	0.1587	--
Log Likelihood	-2556.4933		-2557.4179	

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. N is the number of observations.

In FL we estimate two models: (a) the MIXL with the original cost bids (and then apply the CPI to the resulting WTP estimates) and (b) a MIXL model with the cost bids and the monetary amount of the house loss updated for inflation. Because the CA data was estimated using 2014 data, only one MIXL model is estimated.

In FL (Table 2), the econometric results indicate that coefficients on *risk* and *loss* are statistically significant, but have incorrect signs. Respondents that have no personal experience with fire appear to be confuse on the *risk* and *loss* attributes and tend to focus the program labels. The *risk* and *loss* interaction terms (respondents with personal experience with fire) are statistically significant with the correct signs, i.e., respondents presented with higher risk of damage to their home and higher monetary losses in the survey were more likely to agree to pay for the two programs than those who faced lower risks. In CA (Table 3) the econometric results indicates that the *risk* variable coefficient is statistically significant with incorrect sign. Similarly to FL results, CA respondents with no personal experience with fire are confuse on the *risk* attribute. The *loss* and *loss*personal experience* interaction term are not statistically different from zero. In both FL and CA the coefficient on the *cost* of the program is statistically significant, with the expected negative sign, suggesting internal validity of the results (i.e., the higher the dollar amount households were asked to pay the less likely they were to pay—indicating they were paying attention to the cost of the program to themselves). In both states the alternative specific constants for *public program* and *private program* are statistically significant as are the interactions with risk perception.

Table 3. California Mixed logit (MIXL) 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	Mixed logit Model	
	(mean)	(std. dev.)
risk (%)	0.2543**	0.7889***
	(0.1035)	(0.1511)
risk personal exp.*	-0.3807***	0.3717
	(0.1381)	(0.4223)
loss ($1,000)	-0.0012	0.0513***
	(0.0054)	(0.0064)
loss personal exp.*	-0.0068	0.0205
	(0.0072)	(0.0179)
cost ($)	-0.0021***	--
	(0.0002)	
public program	1.2776***	--
	(0.2184)	
*public pro.*high risk*	1.4399**	--
	(0.6867)	
private program	0.8674***	--
	(0.2317)	
*private pro.*high risk*	1.9589***	--
	(0.6929)	
N	429	--
McFadden R^2	0.2393	--
Log Likelihood	-992.8505	

Note: standard errors in parentheses. ** indicates significance at the 0.05 level, *** indicates significance at the 0.01 level.

Mean WTP Results

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. Using this formula and the wildfire hazard mitigation program parameter estimates from Tables 2 and 3, the one-time mean WTP for a ten year Public and Private programs can be derived for FL and CA homeowners (Table 4).

Table 4. One-time WTP per homeowner for a ten year Public and Private wildfire risk reduction actions and benefit transfer error (2014 Dollars).

	Homeowners			
	Mean WTP Low to Moderate Risk Perception Program		Mean WTP High Risk Perception Program	
	Public	Private	Public	Private
	------------------ (95% Confidence Interval)[a] ----------------------			
California Homeowners	$610 ($429, $792)	$414 ($223, $606)	$688 ($22, $1354)	$936 ($264, $1608)
Florida Homeowners WTP=CPI x MV_0	$831 ($600, $1062)	$427 ($186, $669)	$1,166 ($494, $1838)	$1,561 ($877, $2245)
Florida Homeowners WTP=CPI x $Bids	$832 ($600, $1064)	$422 ($180, $665)	$1,166 ($492, $1840)	$1,566 ($880, $2254)

[a] Krinsky-Robb method using 10,000 draws were used to construct confidence intervals.

Updating Mean WTP Values for Inflation

Rows two and three of Table 4 report the two different approaches for making the WTP values from the 2006 FL data in the same year as the 2014 CA data. There turns out to be little difference between applying the CPI to the marginal values estimated using the original 2006 data and the alternative of applying the CPI to the cost bids prior to estimation of the mixed logit model. Thus, despite the non-linearity in the mixed logit model, the null hypothesis of no difference in results by using either method cannot be rejected, and simply updating the WTP estimates for inflation between the two time periods when performing BT appears to be a reasonable approach.

Differences in Mean WTP Estimates for Low to Moderate Risk Homeowners Compared to High Risk Homeowner

The dollar amounts reported in the second and third columns of Table 4 are the WTP estimates for the Public Program or the Private Program for those respondents who perceive they live in low to moderate fire risk areas. Among households that perceive low to moderate risk, the WTP is quite a bit higher for the Public Program than the Private Program around their home in both CA and FL. Apparently if you perceive a low fire risk you would prefer to reduce fire risk in the forests around the community rather than reducing trees and bushes around your own yard. However, for those households perceiving high wildfire risk, columns four and five indicate a higher WTP for the Private Program around their home rather than in the forests around their community in both CA and FL.

WTP amounts of homeowners that perceive low to moderate risk are lower for both the Public and Private Programs than those homeowners who perceived high risk of wildfire to their home and neighborhood. This difference in WTP is especially true to undertake the Private risk reduction actions around their own home. The higher WTP of homeowners perceiving high risk of damages makes sense as homeowners perceiving high risk likely feel they will benefit more from a given fire risk reduction program than those homeowners that think they are only at low risk of fire.

Discussion

The homeowners in both states appear similar on prior experience with the health effects and travel disruptions associated with wildfires. However, FL's consistently higher WTP than CA, may be consistent with three differences between homeowners in FL and CA. While there appeared to be similar percentages of homeowners in each of the two states that perceived their homes/neighborhoods to be at high risk of wildfire, FL homeowners risk perceptions were statistically higher than CA. As shown empirically in this paper higher perceptions of risk do translate into higher WTP amounts. Further, FL homeowner income was also statistically higher than that of CA.

Another factor that might help explain the differences in WTP between FL and CA is differences in homeowner age. In particular, responding homeowners ages are statistically different between FL and CA, with FL homeowners' age seven years younger than CA homeowners' age. To determine if age was a significant factor in the selection of alternative fire programs, we ran a mixed logit model that interacted age with Public Program and Private Program. In FL these interaction coefficients were negative and significant, but not in CA. In FL older homeowners do have lower WTP. Nonetheless, the higher WTP in FL than CA is consistent with FL homeowners being significantly and substantially younger than CA homeowners.

Conclusions

Identical choice experiment surveys of CA and FL homeowners were conducted to estimate the homeowner WTP for a Public Program to reduce wildfire risk in the neighborhood where they live, and a Private Program to reduce wildfire risk around their home. We adjusted FL 2006 WTP estimates to 2014 using two methods. First method consisted in using the CPI to scale up the estimated 2006 WTP values to 2014. For the second method, we update the "bid" or cost amounts households are asked to pay in the choice experiment by the CPI and re-estimate the model. We find no difference on the method used.

Results show that FL homeowners' WTP for each of the two programs is consistently higher than CA homeowners. We also found similar results as Holmes et al. (2013) that respondents with no personal experience with fire are confused regarding *risk* and *loss* levels presented in the experiment, as the estimate parameters have the wrong sign. In addition, results show that respondents selection is based on the *cost* attribute and anchoring on the fire mitigation program labels.

Overall, the 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 should prove informative to the USFS for targeting cost sharing funds in terms of what types of actions/programs to cost share and in what states to prioritize funding. In particular, the results suggest the order of priority would be to target cost sharing private actions among High Risk Perception households in FL, then private actions by CA High Risk Perception households. These results could help the USFS optimize its allocation of scarce cost sharing funds among states and public vs private actions.

Acknowledgements

The authors would like to thank Dr. Juan Marcos González of Research Triangle Institute for his review comments and suggestions. This research was funded by the USDA Forest Service under Research Joint Venture Agreement 13-JV-11272131064 and Colorado State University Regional Research Project W3133.

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