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**Are WTP Estimates for Wildfire Risk Reductions Transferrable from Coast to Coast?
Results of a Choice Experiment in California and Florida**

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Abstract

With increasingly large expenditures of public funds being spent to reduce the severity of wildfires around homes, officials and legislators are often interested in knowing the economic benefits these funds provide. However, agencies often do not have funding or expertise to conduct individual state specific benefit estimates, and often rely upon benefit transfer (BT) estimates. We calculate the BT error for transferring California homeowner benefit estimates to Florida and vice-versa for public and private fire risk reduction programs. We use the same choice experiment survey and the same specification of the mixed logit model in both states. In terms of accuracy of benefit transfer, among homeowners that perceive low to moderate fire risk, transferring willingness to pay (WTP) from CA to FL or FL to CA for the Public Program to reduce wildfire risk yields a large BT error (-33.1% to 51.8%). However, these large BT errors for the Public Program become smaller (-23.3% to +30.4%) when the benefit transfer focuses on those homeowners with high risk perceptions of wildfire in their neighborhood. In contrast, the opposite pattern is found for the Private Program. There are low BT errors when transferring WTP for the Private Program to reduce risk (-4.4% to 4.8%) between CA and FL homeowners that perceive low to moderate fire risk. But for high risk perceiving homeowners WTP for the Private Program to reduce wildfire risk immediately around their home has a much larger BT error (-16.4% to 31.8%). While our range of BT errors are generally less than found in the BT convergent validity literature, our BT errors are still higher than expected given the same methodology is used in both states, and the homeowners in the two states report similar effects of wildfires and perceived risk. It is hypothesized that the considerable differences between homeowner demographics in the two states may be contributing to the BT errors.

Introduction

Over the last two decades, there has been a large movement of the United States population into Wildland Urban Interface (WUI) areas. This problem is particularly evident in California and Florida, two of the most populous states in the US, and ones with millions of residents living in WUI areas with high or in the case of California, extreme risk of severe wildfires. To reduce 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. Funding limitations makes it imperative for the USFS and State Forestry agencies to know the benefits of these fire risk reduction programs when justifying budget requests to their respective legislatures. Unfortunately it is often not possible for agencies to conduct state specific benefit estimations to accompany their budget requests, and benefit transfer (BT) is often relied upon.

Thus, the purpose of this analysis is to investigate the transferability of homeowner willingness to pay (WTP) to reduce the risk of forest fire in and around where people live. 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 the neighborhood; (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 the house.

We choose the two populous states of California and Florida for the benefit transfer test. 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 California and Florida. This protocol gives the greatest chance for benefit transferability. If benefit transfer does not work well when using the same stated preference method and survey mode, it is likely to work worse in other benefit transfer applications where stated preference valuation method and/or survey modes are typically different.

Literature Review

Our review of the literature will be in two parts, one dealing with the benefit transfer literature and one dealing with forest fuels management to reduce wildfire risk. The relative accuracy of benefit transfer estimates of WTP are usually based on a comparison of transferred values at the target or policy site versus original estimates of the values at the target or policy site. This type of comparison is usually considered a convergent validity test of the benefit transfer.

With dozens of convergent validity tests of benefit transfer estimates, meta-analysis has been performed to summarize the results. The first meta analysis of BT errors in the published literature was by Rosenberger and Phipps (2007). Kaul et al. (2013) recently summarized 31 empirical studies containing over a thousand individual benefit transfer convergent validity tests. In their meta analysis, the relative accuracy of benefit transfer is about 40%. They find that the contingent valuation method (CVM) generates lower benefit transfer errors than does choice experiments (CE), what they call choice modeling in their article. This has implications for our benefit-transfer convergent validity tests as we employ choice experiments. They also find that geographic similarity between the location of the original value estimates (the study site) and the target or policy site has a significant influence on the convergent validity of benefit transfer as

well. This too has implications for our study, as while we believe there is some similarity in the risks of fire in the two states, the demographics of the populations are somewhat different, and hence may undermine convergent validity (Boyle and Bergstrom, 1992).

There have been several CVM surveys of what households would pay for state and county wildfire risk reductions projects in several states including California, Florida and Montana (Loomis and González-Cabán, 2010) and in Colorado (Walker et al., 2007). The wildfire risk reduction projects involved thinning and prescribed burning of the forests in the county where the household resides. 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. Walker et al., estimated household values of \$289 per year for Larimer County, Colorado for these two fuel reduction activities. Loomis and González-Cabán's (2010) CVM studies reported mean WTP per household for prescribed burning for California, Florida, and Montana at \$460, \$392, and \$323 respectively. The mean WTP per household for the mechanical fuel reduction method in California, Florida and Montana was \$510, \$239, and \$189 respectively. Of particular interest for our case study is the comparison of the California and Florida values. 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. None of these studies surveys framed the prescribed burning or mechanical treatment of vegetation as explicitly reducing the risk of fires or expected damages (risk times partial damages) to property. This new study in California and Florida emphasizes fire risk to homes and partial losses to houses. Despite the difficulty with risk communication (see Smith and Desvousges, 1987) we feel that

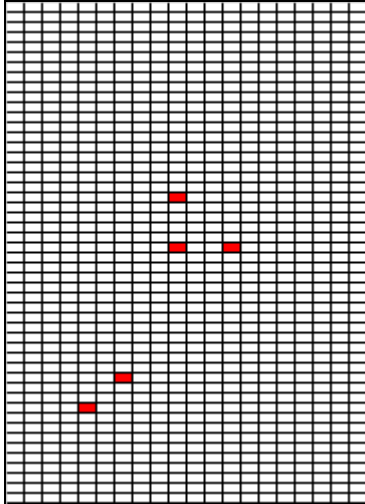
discussing risk to their homes may be a more meaningful way to communicate the potential effects of forest fires on WUI homeowners than just acres burned in the county or state and houses completely destroyed. Thus, focusing on risk of fires to their house and damages might improve the transferability of values between California and Florida.

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 (figure 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 (figure 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).

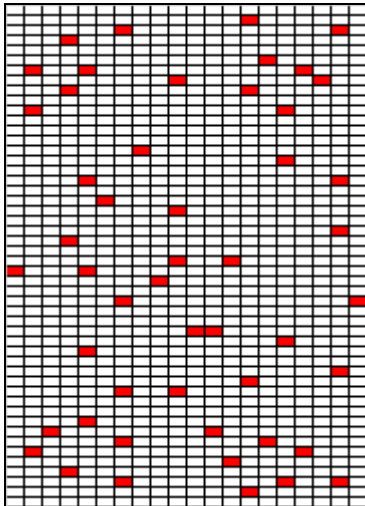
CHANCE GRIDS

(1) UPPER CHANCE GRID: Annual chance



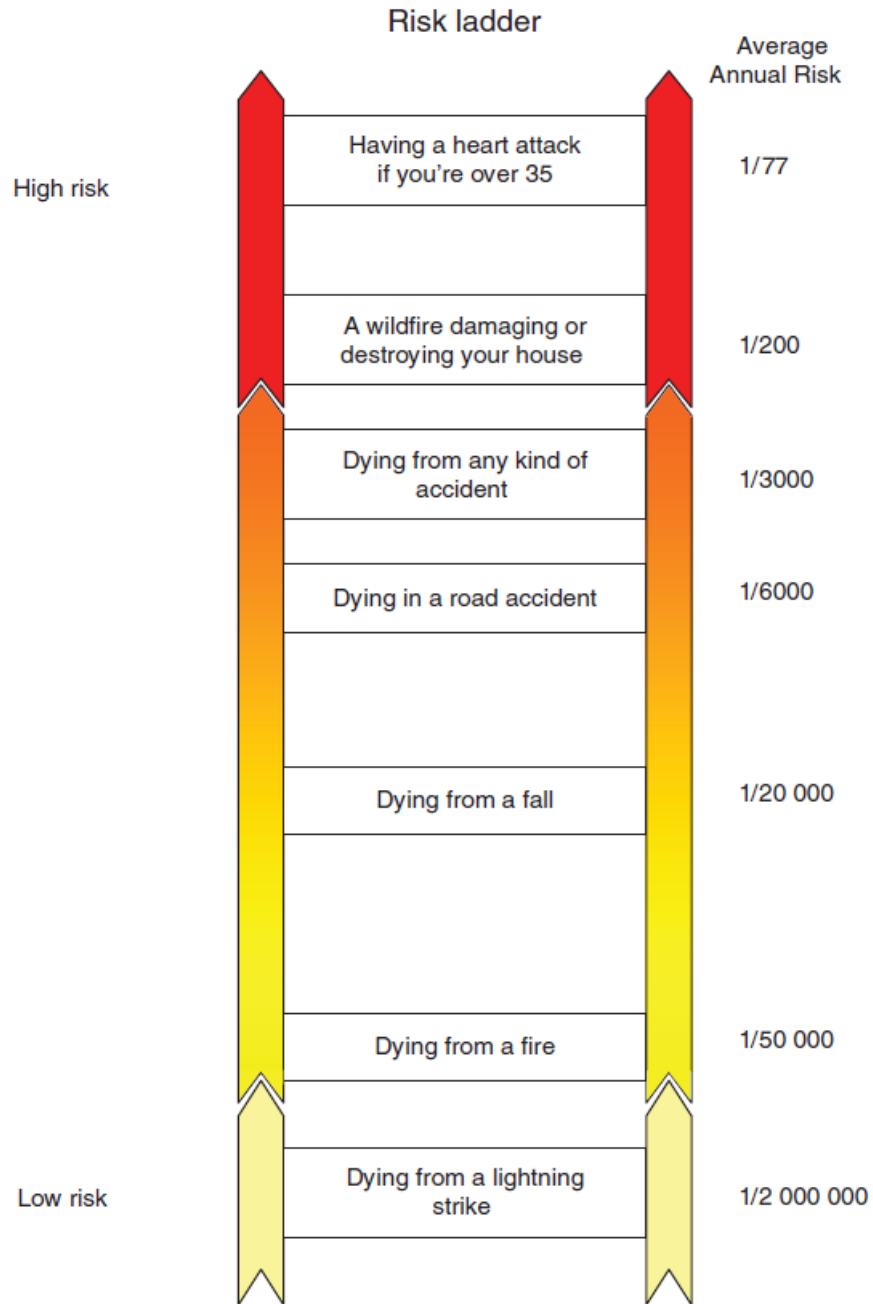
Another way to illustrate the Average Annual Chance of a wildfire damaging your house is shown in the diagram to the left. The “chance grid” shows a neighborhood with 1000 houses, and each square represents one house. The white squares are houses that have not been damaged or destroyed by wildfire, and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



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).

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

The four choice attributes include: (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 associated with no new investments in wildfire protection programs.¹ (2) monetary damage (*loss*) to property from the wildfire; the dollar amounts of the *loss* ranged from \$10,000-\$100,000. (3) expected 10 year loss = chance x damage; attribute #3 is not an independent attribute and was included to facilitate understanding of how risk and damage interacted to give an “expected value” of the damages. (4) onetime *cost* to the household for the ten year program; the *cost* of the programs varied from \$25-\$1,000 for the public program and from \$50-\$1,000 for the private program.

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

¹ We use *italics* to denote variables used in the empirical analysis.

	Alternative #1b	Alternative #2b	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	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Figure 3-- Example of the Choice Set

Data

Stratified sampling of households in the two states was used with more households 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 homeowners providing an address. We obtained 922 usable surveys out of 2000 mailed in Florida for a 46.1% response rate. In California, from 1449 deliverable surveys we obtained 429 usable surveys for a 30% response rate.

The survey responses indicate that when it comes to experience with wildfires the homeowners in Florida and California are quite similar. Homeowners were asked if 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 (*Personal Experience* variable). Forty-three percent (43%) in FL and 46% 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 8% in CA). As can be seen in Table 1, California and Florida respondents were also similar in terms of whether or not they have conducted risk reduction activities on their property. Thus, in terms of experience with wildfire Florida and California homeowners are quite similar.

However, this similarity regarding experience with wildfire contrasts with differences in demographics between homeowners in the two samples, despite a similar sample design. In particular, Florida homeowners have substantially higher household incomes and are younger

than California homeowners, while California homeowners have higher education. Thus the demographic settings between the two areas states are noticeably different, which makes transferability less likely (Boyle and Bergstrom, 1992).

Table 1-- Descriptive statistics of Homeowners in Florida (FL) and California (CA)

Variable	Description	Mean (std. dev.) in FL	Mean (std. dev.) in CA
<i>personal experience</i> (dummy variable)	If either (health related = 1 or travel disruption= 1); else = 0	0.43 (.50)	0.46 (0.50)
<i>fire wise</i> (dummy variable)	Homeowner conducted at least one activity to reduce wildfire risk; if Yes = 1; else = 0	0.76 (0.43)	0.81 (0.40)
<i>high risk</i> (dummy variable)	Respondent indicated that home is located in a high fire risk neighborhood; if Yes = 1; else = 0	0.10 (0.30)	0.08 (0.27)
<i>Age</i>	Respondent's age	57 (14.57)	66 (13.17)
<i>Income</i>	Household annual income	\$77,611 ^a (47,350)	\$51,099 (49,927)
<i>Education level</i>	Respondent's highest education level completed	14.75 (2.33)	15.66 (2.84)

a. Adjusted to 2014.

Econometric Models of Choice Experiment Responses

The standard multinomial logit model (MNL) model 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:

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

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 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:

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

where μ is a scale parameter that is typically set equal to one.²

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 2002). 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:

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

² 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.

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.

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 $f(\beta|\theta)$ where θ is a parameter vector describing the distribution of $f(\bullet)$. Let π_{nj} be the probability that an individual n chooses alternative j from set J , such that

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

where

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

The function $f(\beta|\theta)$ can be simulated using random draws from various functional forms (Train 2002). We use independent 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. In contrast, the latent class (LC) model captures preference heterogeneity for a finite number of heterogeneity classes (Boxall and Adamowicz 2002; Scarpa and Thiene 2005). The preference parameters are specific to each class (c) in a population, and the choice probability for alternative j for each class is:

$$\pi_{n|c}(j) = \frac{\exp(\mu_c \beta_c X_j)}{\sum_{j=1}^J \exp(\mu_c \beta_c X_j)} \quad (6)$$

where C is the set of all classes. The probability that an individual falls within a class is given by a membership function:

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

where γ_c is a scale parameter (set equal to one), and Z_n is a vector of variables describing individual characteristics. The joint probability that an individual belongs to class c and chooses alternative j is simply the product of equations 6 and 7:

$$\pi_{nj}(i) = \sum_{c=1}^C \pi_{nc} \pi_{njc} \quad . \quad (8)$$

This model specifies the choice of an alternative as a function of both the attributes of the alternatives as well as respondent characteristics.

Econometric Results

Initially MNL, MIXL and latent class models (where the classes were distinguished by the presence or absence of *Personal Experience*) were estimated in California and Florida. 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.

Identical specifications of the MIXL models were estimated in California and Florida. The models included two Alternative Specific Constants (ASC), one for the public program (*public pro*) and for the private program (*private pro*). Since 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 California and Florida, coefficients on both of these 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 Florida and Table 3 for California). Further, the

positive signs on the two interaction terms will result in higher WTP for both programs by residents who perceive they live in areas at high risk of wildfire.

Within each state we estimated two models that we label Model I and Model II. The distinction between Models I and II was that Model II also included an interaction term of *personal experience* (either health effects and/or travel disruption) from wildfires with *loss* (damage to house). Model II, also included an interaction term of *Personal Experience* and *risk* as well. We felt that the personal experience of having either health effects or travel disruptions from fire might allow them to make a more realistic assessment of the consequences of wildfires.

In both California and Florida, the basic MIXL is called Model I. This model does not include the interaction variables *risk*personal experience* and *loss*personal experience*; the mean parameter estimates on *risk* and *loss* are not significantly different than zero, although estimates of the standard deviation of parameter estimates on these variables are significant at the 0.01 level. This suggests that these parameter estimates are widely dispersed, and that some proportion (but less than half) of the respondents have parameter estimates with the anticipated sign.

In Florida (Table 2), inclusion of *risk*personal experience*, and *loss*personal experience* in the MIXL Model II results in coefficients on *risk* and *loss*, as well their respective interaction terms being statistically significant. Only respondents with *personal experience* had the expected sign on *risk* and *loss*. In California (Table 3), inclusion of *risk*personal experience* and *loss*personal experience* also results in the *risk* variable being statistically significant with the correct sign. The *loss* interaction term has the expected sign (but the t-statistic is 1.39). In both states, it appears that homeowners with personal experience of wildfire consequences think more

carefully about the expected value of potential losses when making choices regarding wildfire risk reduction programs.

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).

Variable	Mixed logit Model I (mean)	Mixed logit Model I (std. dev.)	Mixed logit Model II (mean)	Mixed logit Model II (std. dev.)
<i>risk (%)</i>	0.034 (0.046)	0.877*** (0.066)	0.119** (0.060)	0.871*** (0.066)
<i>risk* personal exp.</i>	--	--	-0.183** (0.082)	0.009 (0.343)
<i>loss (\$1,000)</i>	0.002 (0.002)	0.042*** (0.003)	0.007** (0.003)	0.042*** (0.003)
<i>loss* personal exp.</i>	--	--	-0.012*** (0.004)	0.002 (0.014)
<i>cost (\$)</i>	-.001*** (0.0001)	--	-.001*** (0.0001)	--
<i>public program</i>	0.924*** (0.161)	--	0.935*** (0.161)	--
<i>public pro.*high risk</i>	1.100*** (0.308)	--	1.131*** (0.308)	--
<i>public pro.*firewise</i>	-0.258*** (0.140)	--	-0.262* (0.140)	--
<i>private program</i>	0.352*** (0.228)	--	0.360*** (0.125)	--
<i>private pro.*high risk</i>	1.453*** (0.311)	--	1.475*** (0.311)	--
N	922	--	922	--
McFadden R ²	0.152	--	0.155	--

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.

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 I (mean)	Mixed logit Model I (std. dev.)	Mixed logit Model II (mean)	Mixed logit Model II (std. dev.)
<i>risk (%)</i>	0.0801 (0.0767)	0.7925*** (0.1035)	0.2131** (0.0891)	0.6117*** (0.1120)
<i>risk* personal exp.</i>	--	--	-0.3098** (0.1335)	0.6607*** (0.2092)
<i>loss (\$1,000)</i>	-0.0023 (0.0044)	0.0526*** (0.0057)	0.0028 (0.0057)	0.0528*** (0.0057)
<i>loss* personal exp.</i>	--	--	-0.0107 (0.0077)	0.0074 (0.0192)
<i>cost (\$)</i>	-.002*** (0.0002)	--	-.002*** (0.0002)	--
<i>public program</i>	1.3467*** (0.3492)	--	1.3997*** (0.3487)	--
<i>public pro.*high risk</i>	2.0742*** (0.7429)	--	1.8482** (0.7299)	--
<i>public pro.*firewise</i>	-0.093 (0.3099)	--	-0.1259 (0.3082)	--
<i>private program</i>	0.7841*** (0.2525)	--	0.8132*** (0.2522)	--
<i>private pro.*high risk</i>	2.5625*** (0.7534)	--	2.3892*** (0.7391)	--
N	356	--	356	--
McFadden R ²	0.226	--	0.234	--

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

WTP Results

Table 4 presents the onetime WTP per homeowner from the Mixed Logit Model I and II. The dollar amounts reported in the first and second columns are the WTP for the Public Program or Private Program for those respondents who perceive they live in low and moderate fire risk neighborhoods. Column 3 and 4 present the WTP for Public Program or Private Program by those who perceived high risk of wildfire to their home and neighborhood. Not surprisingly, those that perceive higher risk are willing to pay more, especially to undertake private risk reduction actions on their own property. In all WTP estimates, WTP by FL homeowners is higher than CA homeowners, typically by about +30%. This finding will influence the benefit transfer error.

Table 4 also reports the relative accuracy of the benefit transfer exercise. For Model I, using FL WTP to infer CA WTP for the **Public** Program to reduce wildfire risk yields a benefit transfer (BT) error of +51.8% (column 1). The error from using CA WTP to infer FL WTP for the **Public** Program to reduce wildfire risk yields a BT error of -34.1%. However, these large BT errors for the **Public** Program become much smaller (+11.8% and -10.5%) when the benefit transfer focuses on those homeowners with high risk perceptions of wildfire in their neighborhood (column 3).

Also for Model I, transferring WTP between CA and FL for the **Private** Program to reduce wildfire risk results in small BT errors for both states (-4.4% to 4.8%--see column 2). Surprisingly, the BT error increases for the **Private** Program when transferring WTP estimates between CA and FL for high risk perceiving homeowners (+19.6% and -16.4%--see column 4).

Table 4. One Time WTP per Homeowner for Public and Private Wildfire Risk Reduction Actions and Benefit Transfer Error (2014 Dollars)

Program	WTP Public Program	WTP Private Program	WTP Public Program	WTP Private Program
Risk Perception Level	Low & Moderate Risk Perception Homeowners	Low & Moderate Risk Perception Homeowners	Hi Risk Perception Homeowners	Hi Risk Perception Homeowners
Mixed Logit Model I: CA	\$679	\$395	\$1,045	\$1,292
BT Error of FL for CA	51.8%	4.8%	11.8%	19.6%
Mixed Logit Model I: FL	\$1,031	\$414	\$1,168	\$1,545
BT Error of CA for FL	-34.1%	-4.6%	-10.5%	-16.4%
Mixed Logit Model II				
<i>Personal* Exp</i> CA	\$697	\$405	\$921	\$1,190
BT Error of FL for CA	49.5%	4.4%	30.4%	31.8%
Mixed Logit Model II				
<i>Personal* Exp</i> FL	\$1042	\$423	\$1,201	\$1,569
BT Error of CA for FL	-33.1%	-4.3%	-23.3%	-24.2%

With regards to Model II, which includes *risk*personal experience* and *loss* personal experience* interaction terms, the BT error is reduced only slightly from Model I for homeowners that perceive low to moderate wildfire risk where they live. However, BT error increases for Model II (as compared to Model I) for high risk perceiving homeowners, for both **Public** and **Private** Programs. Overall the simpler Model I generally have lower BT error among higher risk perceiving homeowners than Model II. There is little difference in BT error between Model I and Model II for low to moderate risk perceiving homeowners.

Another benefit transfer comparison is that of marginal values between Florida and California. In our results, one of the consistently significant marginal values is that of WTP for risk reduction. Dividing the coefficient on risk by the absolute value of the coefficient on costs yields a marginal value of each percentage reduction in wildfire risk. Using the MIXL Model II, the marginal value of a 1% risk reduction is \$107 for California and \$119 for Florida. Thus, on the marginal values the two states have very similar values, hence very transferrable values.

Discussion

Our benefit transfer (BT) errors for total valuation of the **Public** and **Private** Programs are generally within the range found in prior estimates of BT errors (Kaul et al., 2013). When focusing on BT errors of other choice experiments (what Kaul et al. (2013) call choice modeling), our BT error is smaller than 7 other choice experiment BT errors they reviewed and on a par with two other studies. Nonetheless our specific BT error margins are somewhat discouraging. That is, this transfer valued the identical “goods” (in the form of public and private programs), and used identical valuation methods, applied to similar survey valuation questions. The homeowners appear similar on prior experience with the health effects and travel disruptions

associated with wildfires. There were similar percentages of homeowners in each of the two states that perceived their homes/neighborhoods to be at high risk of wildfire. But these similarities appear not to have translated into equivalent preferences toward or WTP for wildfire risk reduction programs. One factor that might explain the differences in WTP between FL and CA is differences in household income. In particular, responding homeowners' household incomes are quite different between FL and CA, with FL homeowners' household income being substantially above CA homeowners' household income. If WTP to reduce wildfire risk is a normal good with respect to income this may explain the higher WTP in FL. It also may be that the geographic "coast to coast" benefit transfer may simply be too much. This would be consistent with the findings of Kaul et al. (2013) that geographic similarity between the study site and the policy site is important. Thus there may be differences in "unobservables" that are driving these differences in WTP.

Whether the transferred benefit estimates have acceptable ranges of error or not depends in part on how precise benefit information needs to be in the budget justification process, and the "opportunity costs" of not targeting scarce wildfire prevention funding in line with the relative values homeowners have for wildfire prevention. In many cases, the benefits of avoiding two or more additional houses in the WUI from burning would offset the costs of conducting an original valuation study.

Conclusions

Identical choice experiment surveys of California and Florida 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. Florida

homeowners' WTP for each of the two programs is always higher than California homeowners, usually by about +30%. This of course has implications for benefit transfer. Thus not surprisingly, use of the Florida homeowners' WTP for California overstates California homeowners' WTP for the public and private programs. Likewise, use of California homeowners' WTP for Florida will understate Florida homeowners' WTP for the two programs.

So what explains the non-trivial differences between California and Florida WTP and the benefit transfer errors? As noted previously, Florida and California homeowners are very similar with regard to having experienced health effects and/or travel delays due to wildfires (43% in FL and 46% in CA). Likewise, very similar numbers of California and Florida homeowners perceived they were in a high wildfire risk area (10% in FL and 8% in CA). However, as seen in Table 1, the sizeable differences in household income between California and Florida may help explain the difference in WTP and the benefit transfer errors. Florida homeowners have higher annual household income, thus have the ability to pay more for wildfire risk reduction programs. However, more research is needed to determine if this relationship between household income and WTP and benefit transfer errors holds up across geographically nearby states with more similar incomes, or whether it is due to unobserved factors associated with living on the southeast coast of the U.S. versus the west coast.

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