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## **Does Distance Impact Willingness to Pay for Forested Watershed Restoration? A Spatial Probit Analysis**

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# Does Distance Impact Willingness to Pay for Forested Watershed Restoration? A Spatial Probit Analysis

## I. Introduction

Forest restoration reduces the probability of catastrophic wildfire and post-fire flooding; it therefore protects the quantity and quality of water in a restored watershed (Mueller *et al.*, 2013). The Four Forest Restoration Initiative (4FRI) is a landscape-scale restoration initiative that plans to restore all of the ponderosa pine forests in a watershed that provides municipal water for residents of Flagstaff, Arizona, a small city in the arid southwestern United States. According to the United States Forest Service, “the overall goal of the four-forest effort is to create landscape-scale restoration approaches that will provide for fuels reduction, forest health, and wildlife and plant diversity.”<sup>1</sup> Treatment plans include timber sales, hand thinning, prescribed burning, and other habitat restoration methods.<sup>2</sup> Flagstaff residents are key beneficiaries of the restoration through potential increases in the quantity and quality of their municipal water supply. In addition, Flagstaff residents will also benefit from reduced catastrophic wildfire and consequent post-fire flood risk.

Many researchers estimate the non-market values of wildfires, wildfire risk, and reduction. For example, Mueller *et al.* (2009) find that proximity to wildfires has a statistically significant decrease in sale price of homes using a hedonic property model. Donovan *et al.* (2007) also apply a hedonic property model to estimate the value of wildfire risk on home values. They compare house prices before and after information on wildfire risk is provided online for 35,000 homes in Colorado Springs, CO. Wildfire risk has a positive correlation with home value before the information is provided, however, the correlation does not remain after information provision. Contingent valuation methods are also applied to estimate values of wildfire reduction (Loomis *et al.*, 2009), values for different treatment options including thinning and prescribed burning (Walker *et al.*, 2007), and prescribed fire (Kaval *et al.*, 2007).

While a large body of research exists investigating the non-market values of catastrophic wildfire and the values of reduction in wildfire risk in high-risk areas, relatively less attention is paid to potential non-market benefits of forested watershed restoration, and none of the contingent valuation studies listed above explicitly control for location of restoration within their estimations. Policymakers face significant constraints when deciding the location of restoration, and it is likely that restoration benefits vary with location. In addition, if respondent behavior is correlated over space, WTP estimates that fail to account for spatial spillover effects may result in inaccurate measures of net benefits for benefit-cost analyses (Loomis and Mueller, 2013). We estimate WTP for forest restoration from dichotomous choice CV data

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<sup>1</sup> <http://www.fs.usda.gov/main/4fri/history>

<sup>2</sup> <http://www.fs.usda.gov/main/4fri/timeline>

using a Bayesian spatial probit incorporating spatial information in both the explanatory variables and the model specification. Our research contributes to the literature in two significant ways. First, we explicitly allow for spatial dependence within WTP estimates from CV data, a method rarely applied in the literature. Second, we directly estimate the impact of distance to restoration area on WTP for forested watershed restoration.

## **II. Methods**

### *Dichotomous Choice Contingent Valuation*

Non-market valuation involves estimating the value of an environmental good or service not commonly bought and sold in a market. Several non-market valuation techniques exist, and most have been applied in some manner to estimate values of forests (Riera *et al.*, 2012). The Contingent Valuation method (CV) is a stated preference method of non-market valuation where respondents are asked to state their preferences for an environmental good or service that is not bought and sold in traditional markets. Many CV studies, including the one presented here, apply the dichotomous-choice elicitation format as recommended by Carson *et al.* (2003). The Dichotomous-Choice CV method involves sampling respondents and asking if they would vote in favor of a referenda and pay a particular randomly assigned dollar amount.

Similar studies have estimated values of non-market water-related ecosystem services using CV. Pattanayak and Kramer (2001) used CV to estimate drought mitigation services provided by tropical forested watersheds in Ruteng Park, Indonesia. Loomis *et al.* (2000) used CV to estimate the value of five water-related ecosystem services on the Platte River in Colorado and found a WTP of \$252 annually per household. In addition, Mueller *et al.* (2013) find irrigators in the Verde Valley in Arizona are WTP approximately \$183 per year for upstream forest restoration of the Verde watershed. While similar studies have estimated the value of water-related ecosystem services, few estimate the value of improvements in water resources following forest restoration for municipal water users, and none have explicitly incorporated distance to restoration.

### *Spatial Probit Model*

Several methods of estimation exist for spatial probit models. For example, spatial probit models have been estimated using full-information Maximum Likelihood (Murdoch *et al.*, 2003 and McMillen, 1992), weighted least squares (McMillen, 1992) and Generalized Method of Moments estimators (Pinkse and Slade, 1998). Classical methods, especially use of Maximum Likelihood techniques, can require hours to estimate small sample problems (LeSage and Pace, 2009). In addition, with classical or non-sampling type estimation procedures, simulation is necessary post-estimation to obtain a distribution of WTP. In contrast,

Bayesian estimation with Markov Chain Monte Carlo (MCMC) simulations and Gibbs sampling provides distributions of the draws of WTP post-estimation without further simulation. We choose the Bayesian methodology for our spatial probit for its relative computational ease in estimation and because Bayesian methods provide post-estimation vectors for parameters that are easily computed into draws for WTP.

Other authors estimate WTP from standard probit models using Bayesian methods, including Mueller (2013, 2014), Mueller *et al.* (2013), Li *et al.* (2009) and Yoo (2004). In addition, Lacombe and Lesage (2013), LeSage *et al.* (2011), Ghosh (2013), and Holloway *et al.* (2002) use Bayesian methods to estimate spatial probit models. Estimates of WTP from contingent valuation studies using spatial probit models are significantly less common in the literature. Loomis and Mueller (2013) estimate WTP for protecting Mexican Spotted Owl habitat, and find that failure to incorporate spatial spillover effects from dichotomous choice contingent valuation may result in policy-relevant differences in WTP estimates.

Bayesian estimation of a spatial probit involves repeated sampling using the MCMC method and Gibbs sampling. We estimate two spatial probit models—the Spatial Durbin Model (SDM) and the Spatial Autoregressive (SAR). The spatial interdependence in the probit model is represented as follows, where  $\mathbf{W}$  is an  $n \times n$  spatial weights matrix,  $\rho$  is the spatial autoregressive parameter,  $y$  is the observed value of the limited-dependent variable,  $y^*$  is the unobserved latent (net utility) dependent variable and  $X$  is a matrix of explanatory variables.

(1)

$$y = \begin{cases} 1 & \text{if } y^* > 0 \\ 0 & \text{if } y^* \leq 0 \end{cases}$$

(2)

$$y^* = \rho \mathbf{W}y^* + \mathbf{X}\beta + \varepsilon$$

for the SAR model. For the SDM,

(3)

$$y^* = \rho \mathbf{W}y^* + \mathbf{X}\beta + \mathbf{W}\mathbf{X}\theta + \varepsilon,$$

where  $\theta$  represents the estimated coefficients on the spatially weighted explanatory variables.

For both models,  $\varepsilon \sim N(0, I_n)$ . If  $\rho = 0$ , the SAR collapses to the standard binary probit model. The spatial probit models relax the strict interdependence assumption used in standard probit models by allowing changes in one explanatory variable for one observation to impact the values of other observations within a neighboring distance as defined by the spatial weights matrix,  $\mathbf{W}$ . Lacombe and Lesage (2013) label the spatial impacts from a spatial probit as direct, indirect and total, and emphasize that failure to properly interpret spatial probit coefficients can result in incorrect conclusions. For example, in a standard probit, marginal impacts are measured by:

(4)

$$\partial E[y|x_r]/\partial x_r = \varphi(\bar{x}_r \boldsymbol{\beta}_r) \boldsymbol{\beta}_r,$$

where  $x_r$  is the  $r$ th explanatory variable,  $\bar{x}_r$  is its mean,  $\boldsymbol{\beta}_r$  is a standard probit estimate, and  $\varphi(\cdot)$  is the standard normal density.

As stated in Lacombe and Lesage (2013), many researchers apply the above formula to interpret coefficient estimates from spatial probit models. However, marginal impacts in a spatial probit take spatial spillover effects into consideration and are no longer scalar. In a spatial probit,

(5)

$$\partial E[y|x_r]/\partial x_r' = \varphi(\mathbf{S}^{-1} \mathbf{I}_n \bar{x}_r \boldsymbol{\beta}_r) \odot \mathbf{S}^{-1} \mathbf{I}_n \boldsymbol{\beta}_r,$$

where  $\mathbf{S} = (\mathbf{I}_n - \rho \mathbf{W})$  and  $\mathbf{I}_n$  is an  $n \times n$  identity matrix. In the spatial probit, the expected value of the dependent variable due to a change in  $x_r$  is now a function of the product of two matrices, whereas in the standard probit, marginal impacts are scalar components. The *direct* impact of changing  $x_r$  is represented by the main diagonal elements of (5), and the *total* impact of changing  $x_r$  is the average of the row sums of (5). Note that the *direct* impact is a function of  $\rho$  and  $\mathbf{W}$ , the spatial autoregressive parameter and the spatial weights, respectively. The *indirect* or spatial spillover effect is the *total* impact minus the *direct* impact. To highlight the necessity of properly interpreting spatial probit coefficients, we compare WTP using coefficient estimates versus using total impacts.

### III. Spatial Weights

As seen in equations (1) – (2) modeling spatial interdependence involves the use of a spatial weights matrix. All spatial spillover and feedback effects work through the spatial weights matrix. Unlike including a distance variable as an explanatory variable, which models the distance from an observation to the habitat or environmental amenity under analysis, the spatial weight matrix models the neighbor relationship between observations. We base our spatial weights matrix on distances between

observations.  $\mathbf{W}$  is an  $n \times n$  weights matrix of the form  $\mathbf{W} = \begin{bmatrix} 0 & \cdots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \cdots & 0 \end{bmatrix}$ . Non-zero elements

represent neighbors. We use a four nearest-neighbors weights matrix. Therefore we have nonzero elements in the spatial weights matrix for the four nearest neighbors to each observations.

### IV. Willingness to Pay Estimates

Following Hanneman (1984), WTP is a function of  $\alpha$ , a “grand constant” and the coefficient on the bid amount following estimation of a standard probit model. We use Log of Bid Amount in the spatial probit and median WTP is therefore obtained by the following transformation:

(6)

$$e^{-\alpha/\hat{\beta}_{Bid.}}$$

In a standard probit, the “grand constant”

(7)

$$\alpha = (\hat{\beta}_1 \times \bar{X}_1) + (\hat{\beta}_2 \times \bar{X}_2) + \dots + (\hat{\beta}_{K-1} \times \bar{X}_{K-1})$$

for all the explanatory variables except for  $\hat{\beta}_{Bid.}$ . Thus, WTP is a function of the estimated coefficients on independent variables and their means.

## V. Estimation

We estimate the SAR and SDM models using Bayesian estimation and Gibbs sampling (Gelfand *et al.* 1990). Following Li *et al.* (2009), let WTP represent a latent variable on  $n$  observations. WTP for an individual is then a function of the explanatory variables,  $\mathbf{X}$ , and the other parameters of interest  $\boldsymbol{\beta}$  and  $\sigma$ .  $\beta_0$  and  $s_0$  are the initial values of the parameters of interest,  $N$  denotes the normal distribution and  $IG$  denotes the inverse gamma distribution. Thus,

(9)

$$WTP^* \sim N(\mathbf{X}'\boldsymbol{\beta}, \sigma^2)$$

and  $\beta$  and  $\sigma$  are independent with

(10)

$$\boldsymbol{\beta} | \sigma^2 \sim N(\beta_0, \sigma^2 \beta_0^{-1})$$

and

(11)

$$\sigma^2 \sim IG\left(\frac{\gamma_0}{2}, \frac{\gamma_0 s_0^2}{2}\right).$$

The Gibbs sampler starts with initial values (in our case, the initial values are set =0) and draws  $\boldsymbol{\beta}$  and  $\sigma$  through simulations. The spatial probit model leads to a multivariate truncated normal distribution (TMVN) for the latent  $y^*$  parameters. Following LeSage and Pace (2009),

(12)

$$WTP^* | \boldsymbol{\beta}, \rho \sim \text{TMVN}\{(\mathbf{I}_n - \rho \mathbf{W})^{-1} \mathbf{X} \boldsymbol{\beta} [(\mathbf{I}_n - \rho \mathbf{W})' (\mathbf{I}_n - \rho \mathbf{W})]^{-1}\}$$

Now, unlike the standard probit, the latent WTP is thus distributed:

(13)

$$\begin{aligned} \boldsymbol{\beta} | \rho, WTP^* &\sim N(c^*, \mathbf{T}^*) \\ c^* &= (\mathbf{X}'\mathbf{X} + \mathbf{T}^{-1})^{-1} (\mathbf{X}'\mathbf{S}y^* + \mathbf{T}^{-1}c) \\ \mathbf{T}^* &= (\mathbf{X}'\mathbf{X} + \mathbf{T}^{-1})^{-1} \\ \mathbf{S} &= (\mathbf{I}_n - \rho \mathbf{W}). \end{aligned}$$

We also need to sample for  $\rho$  using Metropolis Hastings approach. For the approach, (14)

$$\rho|\boldsymbol{\beta}, WTP^* \sim |I_n - \rho\mathbf{W}|\exp\left(-\frac{1}{2}[\mathbf{S}\mathbf{y}^* - \mathbf{X}\boldsymbol{\beta}]'[\mathbf{S}\mathbf{y}^* - \mathbf{X}\boldsymbol{\beta}]\right).$$

We make 20,000 passes through  $WTP^*|\boldsymbol{\beta}, \rho$ ,  $\boldsymbol{\beta}|\rho, WTP^*$ , and  $\rho|\boldsymbol{\beta}, WTP^*$ . We use Gibbs sampling for  $WTP^*|\boldsymbol{\beta}, \rho$ ,  $\boldsymbol{\beta}|\rho, WTP^*$ , and Metropolis Hastings for  $\rho|\boldsymbol{\beta}, WTP^*$ . We omit the initial 19,000 simulations for burn-in. Another benefit of Bayesian estimation is the ability to use posterior probabilities to inform model specification. Following Mueller and Loomis (2010), we choose the model with the highest posterior probability as our final model.

## VI. Data

### *Sample Selection, Focus Group, and Survey Design*

Addresses were obtained from the City of Flagstaff utility records, and were chosen at random ensuring a spatially representative sample. A focus group was held with the City of Flagstaff Water Commission to test and validate the survey instrument. The Flagstaff Water Commission is comprised of local experts, policymakers and stakeholders. A draft of the survey was distributed at a monthly Water Commission meeting. Approximately 20 attendees took an early version of the survey and provided valuable insight. In particular, the focus group help tailor the design of the diagrams in the introduction, and to bound the bid amounts for the WTP question.

Data were obtained from a Dichotomous-Choice Contingent Valuation survey of Flagstaff city residents. The survey was designed using the Dillman Tailored Design Method (Dillman, 2007). A random sample of single family residences were sent a signed cover letter, colored survey booklet, and a return envelope. A reminder postcard was sent, and non-respondents received a second mailing of the survey booklet. Because obtaining accurate estimates requires detailed descriptions of the resources being valued and the contingencies in question (Loomis *et al.*, 2000), the first section of the survey included a watershed map and diagrams of three different watershed condition scenarios. Diagrams displayed three watershed conditions: “Current watershed condition,” “Restored Watershed Condition” and “Watershed Condition Following Wildfire” and the hydrologic responses associated with each watershed condition. Following these diagrams were attitudinal questions about forest restoration, water supply and the WTP question. The last section included demographic questions and solicited respondent’s comments.<sup>3</sup>

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<sup>3</sup> Please see the Appendix for the complete survey.

The WTP question read as follows:

*“Suppose the City of Flagstaff is to propose a referendum requiring residential water users to pay a monthly fee on their water bill. By law, all funds would go directly to monitoring and maintaining the forest health of the Lake Mary and Upper Rio de Flag watersheds.*

*If the water user contribution program were to cost you an additional X \$ per month, would you vote in favor of the referenda?”*

where “X” equals a random bid amount inserted into surveys. Bid amounts ranged from \$1 to \$20, weighted with higher frequencies from \$1-\$8 and lesser frequencies from \$9-\$20.

#### *Respondent Certainty*

After the WTP question, respondents were asked to rank the certainty of their response on a scale of 1 to 10, where 1 is “Not at all certain” and 10 is “Completely certain.” Hypothetical bias occurs when respondents answer a hypothetical question in a way that is inconsistent with their actual behavior, thus resulting in biased WTP estimates. While respondent uncertainty results in hypothetical bias, little theoretical guidance exists in explaining why respondents are uncertain (Akter *et al.*, 2009). To investigate hypothetical bias, Champ and Bishop (2001) performed a split sample experiment where some respondents were asked their WTP to invest in wind energy for one year, while others were offered a hypothetical opportunity. Champ and Bishop (2001) found evidence of hypothetical bias—the WTP of the respondents with the hypothetical opportunity was higher than those with the actual investment opportunity. However, when respondents who were less certain of their answer to the hypothetical WTP question were coded as voting “no,” the hypothetical bias was eliminated. Therefore, we choose to follow the approach suggested in Champ and Bishop (2001), and applied by Li *et al.* (2009), Mueller (2013, 2014), and Mueller *et al.* (2013). We re-code respondents with certainty levels less than 8 out of 10 as voting “No” for the WTP question.

#### *Spatial Variables*

A unique focus of our study is including distance-related variables as predictors of WTP. We calculated the distance to the City Hall, a proxy for city center, as well as the distance to the nearest proposed treatment area. The average respondent household was 2.7 miles from the city center, and within less than one mile of the nearest treatment area. In general, real estate near the downtown area is priced at a premium, so we use distance to City Hall as a neighborhood proxy. In addition, most households within our sample are located within walking distance to a proposed 4FRI treatment area, highlighting the potential importance of restoration to our respondents.



## VII. Calculation of WTP

We predict WTP as a function of the following explanatory variables:

- *Importance of Wildfire Prevention*: the relative importance of wildfire prevention (5 point Likert Scale)
- *Threat of Drought*: concern for threat of drought (5 point Likert Scale)
- *Distance to City Center*: distance from respondent's home to city center (miles), as a proxy for neighborhood quality.
- *Distance to Nearest Treatment Area*: distance from respondent's home (miles) to the nearest 4FRI treatment area.

We estimate WTP using both the traditional method of estimated coefficients and by including *Total Effects*. For the traditional method:

(15)

$$\begin{aligned} \alpha_{\text{Marginal Effects}} = & +(\hat{\beta}_{\text{Wildfire Prevention}} \times \bar{X}_{\text{Wildfire Prevention}}) + \\ & (\hat{\beta}_{\text{Threat of Drought}} \times \bar{X}_{\text{Threat of Drought}}) + \\ & (\hat{\beta}_{\text{Distance to City Center}} \times \bar{X}_{\text{Distance to City Center}}) + \\ & (\hat{\beta}_{\text{Distance to Treatment Area}} \times \bar{X}_{\text{Distance to Treatment Area}}), \end{aligned}$$

where  $\hat{\beta}$  are the estimated coefficients from the spatial probit.

We also use total impacts for the following:

(16)

$$\begin{aligned} \alpha_{\text{Total Effects}} = & +(\hat{T}_{\text{Wildfire Prevention}} \times \bar{X}_{\text{Wildfire Prevention}}) + \\ & (\hat{T}_{\text{Threat of Drought}} \times \bar{X}_{\text{Threat of Drought}}) + \\ & (\hat{T}_{\text{Distance to City Center}} \times \bar{X}_{\text{Distance to City Center}}) + \\ & (\hat{T}_{\text{Distance to Treatment Area}} \times \bar{X}_{\text{Distance to Treatment Area}}), \end{aligned}$$

where  $\hat{X}$  are the *Total Impacts* from the spatial probit.

## VIII. Results and Discussion

### *Response Rate*

490 surveys were mailed with 120 responses and 48 un-deliverables, resulting in a response rate of 24%. A 24% response rate is similar to other Contingent Valuation studies using mail surveys. For example, Walker *et al.* (2007) have an average overall response rate of approximately 30%, Mueller (2013) reports a response rate of 26%, and Mueller *et al.* (2013) report a response rate of 32%.

### *Attitudinal Variables*

Respondents were asked, “Considering the full range of issues you face, how important is watershed health to you? On a scale of 1 to 5, where 1 indicates “Not Important” and 5 indicates “Extremely Important,” circle one.” The mean response was 3.97, indicating that watershed health is a high priority for respondents. Respondents were also asked, “Considering the full range of issues you face, how important is wildfire prevention to you? On a scale of 1 to 5, where 1 indicates “Not Important” and 5 indicates “Extremely Important,” circle one.” The mean response was 4.52, indicating that wildfire prevention has a relatively high priority within the sample.

Respondents were also asked to indicate how concerned they are about threats to the Lake Mary and Upper Rio de Flag Watersheds including:

- Wildfire
- Drought
- Flooding
- Global Climate Change

On a scale of 1 to 5, where 1 indicates “Not at All Concerned” and 5 indicates “Extremely Concerned,” respondents are the most concerned about wildfire and drought.

### *Respondent Certainty*

Respondents were asked, “On a scale of 1 to 10, with 1 being not at all certain and 10 being completely certain, how certain are you of your answer” to the WTP question. 70% of respondents chose a Certainty level of 8 or above on their answer to the WTP question. We follow the approach outlined in Champ and Bishop (2001) discussed above and re-code responses with a certainty level of 7 or less as “No” votes on the WTP question to reduce hypothetical bias.<sup>4</sup>

### *Willingness to Pay*

Regression results are presented in Table 1. We find a strong and statistically significant negative estimated coefficient on the Log of Bid Amount, which is expected with Dichotomous Choice CV results. We also find that the estimated coefficient on the Importance of Wildfire Prevention is positive and statistically significant. Our summary statistics indicate that the Importance of Wildfire Prevention is at the forefront of respondents’ concerns. The positive and strong statistical significance of Importance of Wildfire Prevention in our WTP equation also indicates that respondents who view Wildfire Prevention as more important are also more likely to be WTP to support forested watershed restoration efforts.

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<sup>4</sup> It is important to note that the high certainty of our respondents may indicate that respondents who feel strongly about water issues were more likely to complete our survey. As noted in the methods section, we follow the Dillman Tailored Design method in order to mitigate non-response bias. However, no other additional tests were done for non-response bias, and this remains a useful avenue of further research, especially with spatial probit models.

We also find a positive and statistically significant estimated coefficient on Threat of Drought. Respondents who view the Threat of Drought as relatively important are more likely to be WTP to support forested watershed restoration efforts. From a policy perspective, this result provides insight that respondents connect forest restoration and drought prevention. Understanding this connection is a key aspect of gaining public support for restoration efforts.

We find a negative and statistically significant estimated coefficient on Distance to City Center. The negative coefficient indicates that as distance to the city center increases, the probability that a respondent is WTP for restoration decreases. Our Distance variable is also a proxy for neighborhood quality and other demographic variables. Most of the wealthiest neighborhoods within our sample are located close to the city center.

Finally, we find a positive and statistically significant estimated coefficient on Distance to Treatment Area. In other words, as Distance to Treatment Area increases, the probability of a “Yes” vote on the WTP question increases, holding all other explanatory variables constant. At first glance, this result seems counter-intuitive. In fact, a 2006 study in Flagstaff estimated that reducing forest canopy would increase property values using the hedonic property method (Kim and Wells, 2006). Thus, while we obtain a positive median WTP for restoration, respondents who live closer to proposed treatment areas are actually less likely to be WTP for that restoration, holding all other variables in the model constant. Thus, we may have evidence of a Not In My Backyard (NIMBY) syndrome in Flagstaff, where residents are generally in favor of forest restoration, yet prefer the restoration to be further away from their home. Another potential challenge is that the restoration does involve thinning and prescribed burning, and residents may not want to experience the negative effects of these restoration activities, including noise and smoke. We believe that the negative coefficient also provides insight into another potential area of further research within the forested watershed restoration literature—investigating the potential short-term negative impacts of restoration combined with the long term benefits. Another potential reason for the apparent contrast in our results relative to using revealed preference models is that our sample includes single family residents, however it includes both renters and owners. Therefore, renters may not be considering the potential capitalized value of the forest restoration in terms of home values, and solely considering potential noise and smoke issues.

We calculate two estimates of median WTP. One is a function of the estimated regression coefficients in the probit model, and the other incorporates total impacts and therefore total spatial spillovers. We find median WTP to be significantly higher without consideration of spatial spillovers, at \$9.56. In contrast, median WTP is \$1.56 using the total effects coefficients. However, it is important to note that many of the total effects are not statistically different from zero. This is also represented in the 0.212 p-value on the  $\rho$  parameter. While the posterior probabilities do

indicate that the SAR with 4 nearest neighbors is the best model, we do have evidence that the spillover effects are relatively weak.

**Table 1: Spatial Probit Regression Results**

<b>Variable</b>	<b>Regression Coefficient</b>	<b>Coeff. p-level</b>	<b>Total Effect</b>
<i>Constant</i>	-3.6422	0.001	0.1299
<i>Log of Bid Amount</i>	-0.5176	0.008	0.1134
<i>Importance of Fire Prevention</i>	0.6111	0.002	-0.0684
<i>Threat of Drought</i>	0.5487	0.021	0.1416
<i>Distance to City Center</i>	-0.3292	0.024	0.1299
<i>Distance to Treatment Area</i>	0.6802	0.027	0.1134
$\rho$	-0.2827	0.224	-0.0684
Median WTP using Regression Coefficients	\$9.56		
Median WTP using Total Impacts	\$1.84		

## IX. Conclusions

Flagstaff has approximately 22,836 households.<sup>5</sup> If our median estimate approximates the WTP for the average Flagstaff household, our model predicts monthly benefits of restoration of approximately \$42,000 when including total impacts. Failure to account for spatial spillovers results in a much higher benefits estimate of \$218,000. Therefore, we find policy-relevant differences in WTP when taking spatial spillover effects into account. We also find negative and statistically significant estimated coefficients on Distance to Treatment Area, indicating that while the average respondent is WTP to support forest restoration, they are less likely to support restoration in areas closer to their property.

While the relationship between restoration and forested watershed health is well established in the literature (Mueller et.al 2013), funding for restoration remains a significant constraint. Thus, estimates of the benefits of restoration are essential for efficient decision-making. While much research exists estimating the non-market value of wildfire, less research exists estimating the value of forested watershed restoration, and no studies explicitly model WTP for forested watershed restoration using a spatial probit. We apply a Bayesian spatial probit and also include distance variables in our WTP equation. Our results indicate that careful consideration of the spatial dimension of WTP data may be necessary in order to ensure accurate WTP estimates from dichotomous choice CV models.

<sup>5</sup><http://factfinder2.census.gov/faces/tableservices/jsf/pages/productview.xhtml?src=CF>

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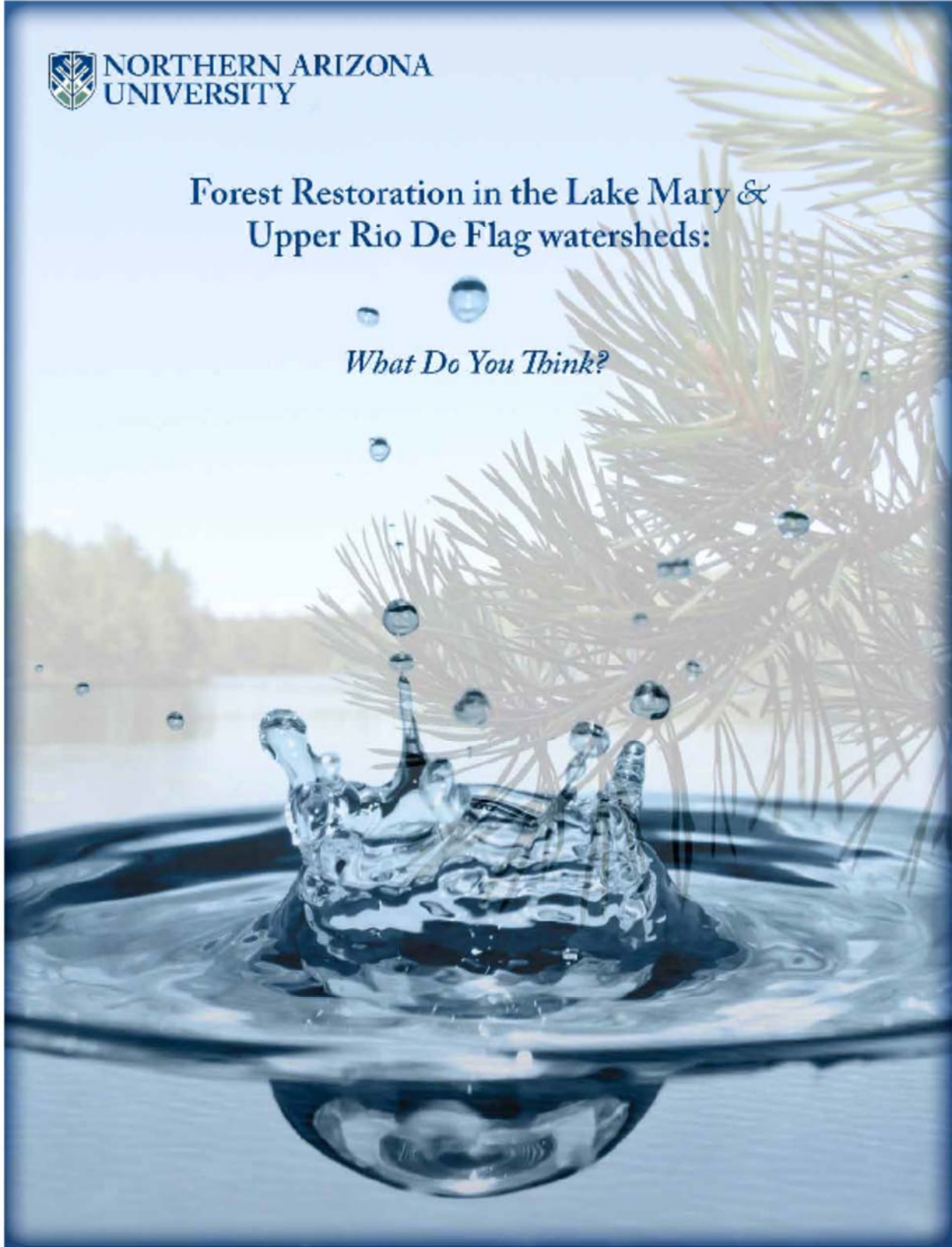
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XI. Appendix



Forest Restoration in the Lake Mary &  
Upper Rio De Flag watersheds:

*What Do You Think?*



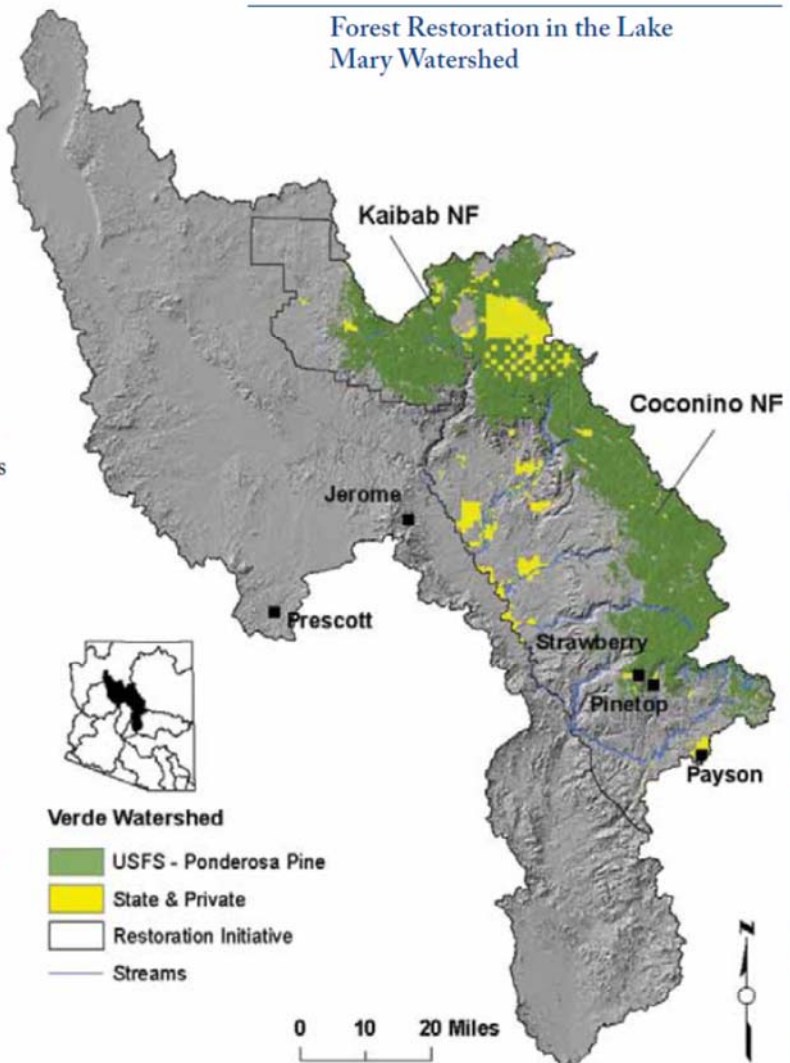


## Forest Restoration and Your Watershed

*What do you think?*

The Four Forest Restoration Initiative (4FRI) is a collaborative project involving the USDA Forest Service partnering with forest products industries, state agencies, non-profit organizations, and others working to restore 2.4 million acres of ponderosa pine forests in Northern Arizona. Most of the ponderosa pine forests in the Lake Mary and Upper Rio de Flag watersheds are planned for restoration treatments. Forest restoration will occur in a two-part process: mechanical thinning of small diameter trees and follow-up burning of surface fuels. Researchers expect that these forest restoration treatments will enhance watershed services. Watershed services are defined as the benefits obtained from a watershed and include reduced flood hazard, enhanced water yield, and maintenance of water quality through reduced fire risk. As a recipient of water from the Lake Mary watershed, we are interested in your opinion about forest restoration and its impact on watershed services.

Forest Restoration in the Lake Mary Watershed





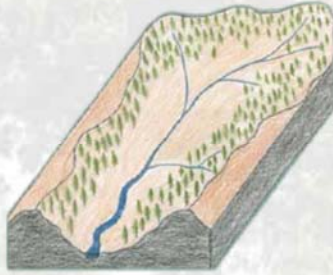
Consider the following watershed conditions and how they impact water supply.

Current Watershed Condition



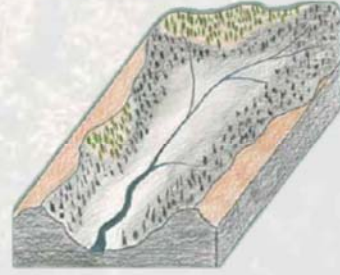
- Limited water yield
- Reduced groundwater recharge
- High density of trees and risk of catastrophic wildfire
- Present day flows

Restored Watershed Condition



- Enhanced water yield
- Enhanced groundwater recharge
- Historical density of trees and reduced risk of catastrophic wildfire
- Improved spring snowmelt flows

Watershed Condition Following Wildfire



- Irregular water yield
- Restricted groundwater recharge
- Increased flood potential
- Reduced water quality
- Increased sedimentation

Forested watersheds play an important role in water supply. Research suggests that forest restoration in the Lake Mary watershed will enhance watershed services. These services include:

- Enhanced water yield (quantity)
- Enhanced water quality
- Enhanced groundwater recharge
- Reduced seasonal and annual variability
- Reduced risk of catastrophic wildfire
- Regularity of flows
- Reduced flood risk

Next ==> ==> ==> ==> ==> ==>

1. Prior to this survey, were you aware of the Four Forests Restoration Initiative?

YES     NO

2. Do you believe that forest restoration activities will have a positive effect on watershed services in the Lake Mary and Upper Rio de Flag watersheds?

YES     NO

3. To what degree do you feel that forest restoration activities will positively affect watershed services? On a scale of 1 to 5, where 1 indicates "Not at All", and 5 indicates "Very Strongly", circle one.

Not at All =>> Weakly =>> Moderately =>> Strongly =>> Very Strongly  
1            2            3            4            5

4. Considering the full range of issues you face, how important are water sustainability issues to your household? On a scale of 1 to 5, where 1 indicates "Not Important" and 5 indicates "Extremely Important", circle one.

Not Important =>> Slightly Important =>> Moderately Important =>> Very Important =>> Extremely Important  
1                    2                    3                    4                    5

5. Considering the full range of issues you face, how important is catastrophic wildfire prevention to you? On a scale of 1 to 5, where 1 indicates "Not Important" and 5 indicates "Extremely Important", circle one.

Not Important =>> Slightly Important =>> Moderately Important =>> Very Important =>> Extremely Important  
1                    2                    3                    4                    5

6. On a scale of 1-5, where 1 is "Not Concerned", 2 is "Slightly Concerned", 3 is "Moderately Concerned", 4 is "Very Concerned" and 5 is "Extremely Concerned", please indicate how concerned you are about each of the following threats to the Lake Mary watershed? Circle one.

a. Catastrophic Wildfire    Not Concerned =>> =>> =>> =>>Extremely Concerned  
1   2   3   4   5

b. Drought    Not Concerned =>> =>> =>> =>>Extremely Concerned  
1   2   3   4   5

c. Flooding    Not Concerned =>> =>> =>> =>>Extremely Concerned  
1   2   3   4   5

d. Global Climate Change    Not Concerned =>> =>> =>> =>>Extremely Concerned  
1   2   3   4   5

e. Other Serious Threats. Please describe.

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## Your Chance to Vote

7. As mentioned above, the projected benefits of the Four Forest Restoration Initiative are enhanced groundwater recharge, increases in surface water quality and quantity, and reduced threats to existing watershed services from catastrophic wildfire and climate variability. Although the United States Forest Service and partnering industries will finance the initial mechanical thinning, funding remains uncertain for follow-up maintenance, monitoring, and burning activities. Follow-up treatments are critical for sustaining and protecting important watershed services. As beneficiaries of increased watershed services, water users may have the opportunity to contribute funding for restoration treatments that sustain watershed services.

Suppose the City of Flagstaff is to propose a referendum requiring residential water users to pay for forest restoration. All funds would go directly to maintaining the forest health of the Lake Mary and Upper Rio de Flag watersheds. If the referendum were passed, water users would be charged an additional fee per month on their water bills. By law all fees collected would be spent on forest restoration activities that would improve watershed services.

If the water user contribution program were to cost you an additional \_\_\_\_\_ \$ per month, would you vote in favor of the referenda?

YES       NO

On a scale of 1 to 10, with 1 being not at all certain and 10 being completely certain, how certain are you of your answer to question 7 above?

Not at All Certain => => => => => => => => => Completely Certain

1 2 3 4 5 6 7 8 9 10

8. If you answered "no" to the above question, please indicate your reason why: Circle one.

- a. Water resources are not that important to me.
- b. I cannot afford to pay.
- c. It is unfair to expect me to pay for improvements in watershed services.
- d. Forest restoration is not the solution to safeguarding and/or enhancing water resources.
- e. The federal government should be paying for watershed restoration on federal lands.
- f. I am opposed to paying for watershed services.
- g. Other \_\_\_\_\_

Next => => => => => =>

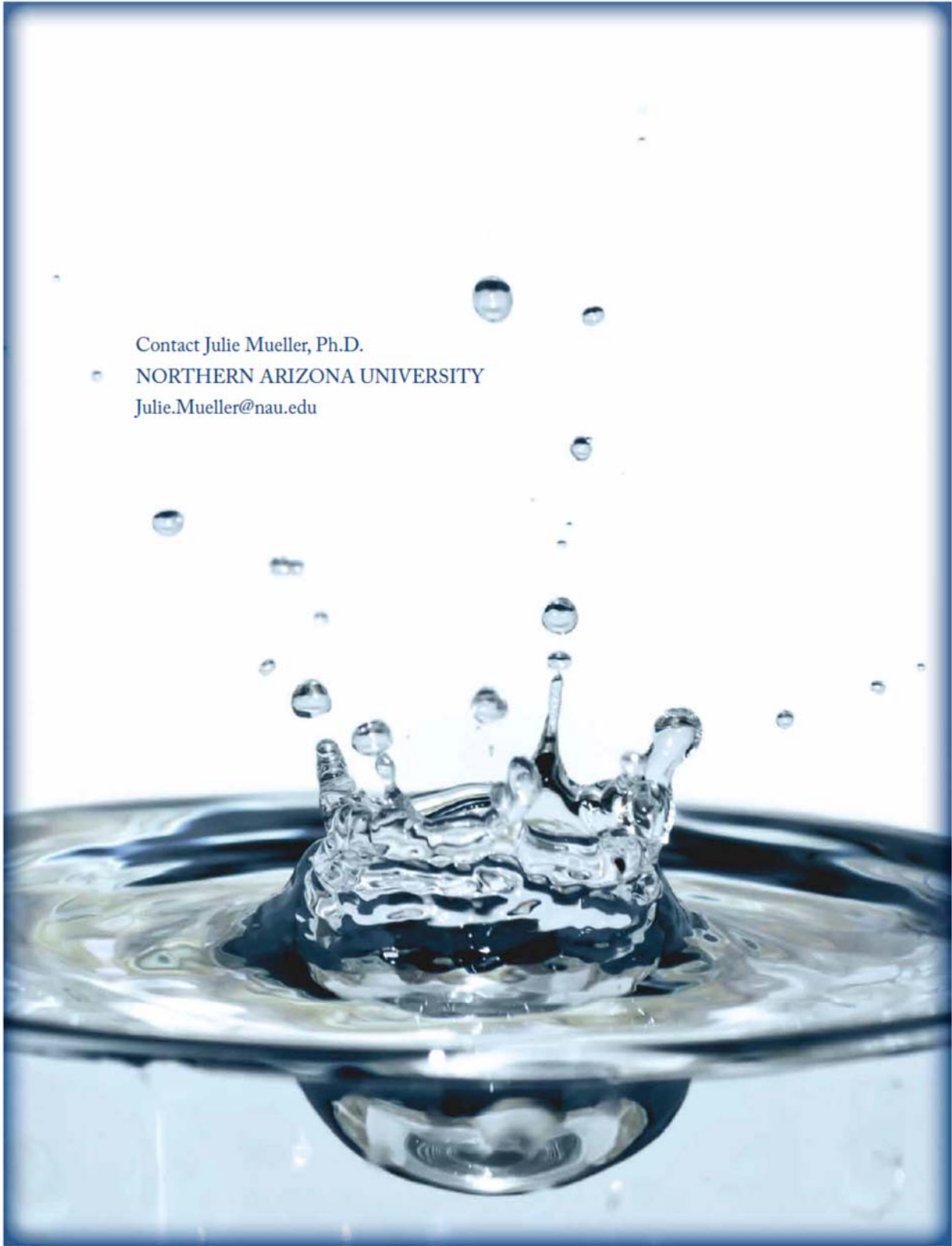


## About You

The last few questions will help us in evaluating the representativeness of our sample. Your answers are STRICTLY CONFIDENTIAL and will not be used to identify you in any way.

9. Are you \_\_\_\_\_ Male \_\_\_\_\_ Female
10. What is your zip code? \_\_\_\_\_
11. What is your age? \_\_\_\_\_ # of Years
12. Did you vote in the last election?  
 YES  NO
13. Are you currently a member of an environmental or conservation organization?  
 YES  NO
14. Is your ethnic background (circle one)
- |                       |                              |
|-----------------------|------------------------------|
| a. Native American    | d. Black or African American |
| b. Asian              | e. White or Caucasian        |
| c. Hispanic or Latino | f. Other                     |
15. What is the highest **year** of formal schooling you have completed?  
0 1 2 3 4 5 6      7 8 9      10 11 12      12 14 15 16      17 18 19 20  
(Elementary)    (Junior High)    (High School)    (College or    Graduate Technical School)
16. How many people are there in your household sharing the same budget?  
\_\_\_\_\_ # of People
17. Of those people, how many earned money last year?  
\_\_\_\_\_ # of People
18. Including all the people from question 16, what was your household income (before taxes) last year?
- |   |  |  |  |  |
|---|--|--|--|--|
| <input type="checkbox"/> Less than \$20,000     | <input type="checkbox"/> \$20,000-29,999 | <input type="checkbox"/> \$30,000-39,999 | <input type="checkbox"/> \$40,000-49,999 | <input type="checkbox"/> \$50,000-59,999   |
| <input type="checkbox"/> \$60,000-69,999        | <input type="checkbox"/> \$70,000-79,999 | <input type="checkbox"/> \$80,000-89,999 | <input type="checkbox"/> \$90,000-99,999 | <input type="checkbox"/> \$100,000-149,999 |
| <input type="checkbox"/> Greater than \$150,000 |  |  |  |  |





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