DISSERTATION

GEOGRAPHIC DIFFERENCES IN CONTINGENT VALUATION SURVEY RESPONSES: AN APPLICATION TO FOREST FIRE PREVENTION PROGRAMS IN USA AND VIETNAM

Submitted by

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WE HEREBY RECOMMEND THAT THE DISSERTATION PREPARED UNDER OUR SUPERVISION BY HUNG TRONG LE ENTITLED "GEOGRAPHIC DIFFERENCES IN CONTINGENT VALUATION SURVEY RESPONSES: AN APPLICATION TO FOREST FIRE PREVENTION PROGRAMS IN USA AND VIETNAM" BE ACCEPTED AS FULFILLING IN PART REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

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ABSTRACT OF DISSERTATION

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Benefit measures are helpful in designing efficient environmental policy, and the question on how to determine benefit measures is a major concern for environmental economists. Because of this, the use of these measures in benefit transfers from one study area to another has become prevalent in policy analysis.

The first purpose of this study is to find out how much residents in the three very distinct states of California, Florida and Montana, support prescribed burning and mechanical fire fuel reduction techniques through a contingent valuation method. We test whether the willingness to pay per household is similar or not and whether the willingness to pay functions are transferable between three states. The next purpose is to test whether willingness to pay for fire fuel reduction programs is sensitive to acreage reduction or not. Finally, we investigate the feasibility of applying contingent valuation method to value forest fire prevention in Vietnam.

Available data reveal that from 70% to 98% of people agreed to pay the proposed bid amounts and that fire fuel reduction programs are highly supported in three states of California (CA), Florida (FL) and Montana (MT). With Chi-square test, we found that response rates of white and Hispanic people for support of prescribed burning and mechanical fire fuel reduction programs are not different from each other and no significant difference exists among white and Hispanics people in three states CA, FL and MT in the pattern of protest and non protest reasons for refusing to pay for these programs. White people in CA, FL and MT have the means of willingness to pay of \$416.95, \$305.04, \$328.08 for prescribed burning program and \$402.97, \$229.74, \$207.94 for mechanical fire fuel reduction program, respectively. For Hispanic people, the means of willingness to pay for prescribed burning program in California and Florida are \$991.84 and \$393.36 and for mechanical fire fuel reduction program. The mean of willingness to pay of \$397.5 has been found for Florida. With wide confidence intervals, willingness to pay by white and Hispanic people in three states is similar to each other and these willingness to pay functions are transferable among these states. The contingent valuation method is applicable to the forest fire prevention program in Vietnam context with working days contribution. Money willingness to pay is found to be unrealistic for this program.

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1. INTRODUCTION

On August 20, 2002 President George W, Bush approved the Healthy Forests Initiative aiming on restoration of health of forests and rangelands in the western United States. It affirms that the American people, their property and environment, particularly the forest and rangelands of the West are threatened by catastrophic fires and environmental degradation. Hundreds of millions trees and invaluable habitats are destroyed each year by these severe wildfires. During 2000-20002, the United States experienced its worst two fires seasons in a half century. The 2002 fire season experienced forest fires that burned a total acreage that was larger than the state of Maryland and Rhode Island combined (White House press release, 2003). Hundreds of communities have been affected by these wildfires. Ten thousands of people have been evacuated from their homes, and thousands of structures have been destroyed (George Bush, 2003). Fires harm people and local communities, disrupt local economies, damage environment, and increase air pollution. Forest fires now burn at greater speed and intensity than before due to unnatural build up of fuels from past fire. The Forest Initiative provides several avenues to curb the extent and severity of wildfires. To restore the health of forests and rangelands, President Bush is seeking : *first* to improve procedures for developing and implementing fuel treatment and forest restoration projects in collaboration with local government, *second* to develop guidance for weighing the short term risks against the long term benefits of fuel treatment and restoration projects, *third* to develop guidance to ensure consistent national environment policy act (NEPA) procedure for fuel treatment activities and restoration activities including development of a model of environmental assessment for these types of projects.

Two main fuel treatment methods are: the prescribed burning method and the mechanical fire fuels reduction method (Bush, 2002). Nash in "Fireproofing the Forests" believed that these methods are the best strategies for ensuring that the present forests survive into the future. The prescribed burning method is defined as the controlled application of fire to existing naturally occurring fuels under specified environmental conditions following appropriate precautionary measure (Florida Division of Forestry, 2000). This practice allows the fire to be confined to predetermined area and accompanied the planned land management activities. The public benefits from prescribed burning are: fuel reduction for fire protection, site preparation for reforestation, improvement of livestock forage, control of forest diseases, maintenance and restoration of desired plant and animal communities. Prescribed burning reduces the number of wildfires, acres burned and average acres per wildfire. However, it does not eliminate the threats of wildfire, only ameliorates its effects (Koehler, 1999). Using prescribed burning will create certain emissions in the surrounding air. These emissions affect local air quality. In addition to temporarily reducing air quality, prescribed burning can also decrease visibility. This is a primary concern with respect to road-rights-of –way (Florida Department of Forestry, 2000). Property damage of this method also is to be considered. The possibility of property damage and threat to personal safety from prescribed fire is greatest if the fire escapes the area where the prescription boundaries have been this situation, the resulting wildfire is very dangerous, and should be brought under control as quickly and safely as possible. The possible effects of prescribed fire may also include negative effects to environment, e.g., to timber, local ecosystem, air quality, wildlife, watershed and others. Therefore, prescribed burners should be aware of what procedures to follow.

The mechanical fire fuel reduction method consists of mechanically removing smaller trees and vegetation. It then creates mulch that acts as a barrier to the vegetation found on the forest floor, which reduces vegetation for wildlife (Ellingson, 2003). This mechanical fuel reduction method is especially effective at lowering the height of vegetation, which reduces the ability of fire to climb from the ground to the top or crown of the trees. This mechanical fire fuel reduction method does not produce any smoke. However, it is more expensive than the prescribed burning method due to increased labor and equipments needed and is not as environmentally sound (Kuypers, 1999). It would also decrease the number of ground level plant species that are food for wildlife.

In addition to President Bush's Forest Initiative, California's forest plan also has been approved seeking to reduce total costs and losses from wildfire in California by protecting assets at risk through focused pre-fired management prescription and increasing initial attack success. The main objective of this plan is to create wildfire protection zones that reduce the risks to citizens and firefighters; to access wild lands, not just the lands of state responsibility; to identify and analyze key policy issues and develop recommendations for changes in public policy; to have a strong fiscal policy focus and monitor the wild land fire protection system.

Prescribed burning and mechanical fire fuel reduction programs (hereafter RX and Mech programs) have been recognized to be important in government wild fire control programs. However, acceptance of residents in the project areas plays an important role in successful implementation of these programs (Toman, and Shindler, 2003). There exist many factors that contribute to public acceptance of prescribed burning and mechanical fire fuel reduction programs. This includes public knowledge, information source, and trust in agencies and relationship between residents and forest service. Therefore, people do not always recognize these programs as solutions. Kuypers (1999) thought the success of these programs could be lowered in the case of severe smoke from prescribed burning, suffering health problems, and ash in swimming pools.

Prescribed burning and mechanical fire fuel reductions could be perceived differently in different states of the US. This may be because of various factors such as income levels, education on these programs, and race difference in the population. This may lead to differences in willingness to pay for these programs.

The main purposes of this study are to find out how much residents in the three very distinct states of California, Florida and Montana, support prescribed burning and mechanical fire fuel reduction techniques through using contingent valuation method (henceforth CVM). While each state has forests, they represent very different geographic regions of the country. Understanding this aspect is important for policy makers and resource managers, so they may know whether support for these two methods is similar across states or not. If not similar, then national policies will need to be tailored to each state or geographic region of the country. The second purpose is to determine if willingness to pay (hereafter WTP) per household is similar and whether the WTP functions are transferable between the three states. If they are not similar, not transferable, then surveys will have to be conducted in each geographic region to understand the benefits of these two fire prevention methods. As a part of this test, we compare WTP of whites/Caucasians and Spanish speaking Hispanics. Another purpose of this analysis is to conduct a scope test to determine whether WTP increases with the number of acres protected per household. The scope test is one of the internal validity tests of CVM suggested by the NOAA panel (Arrow *et al.*, 1993).

Finally, we investigate the feasibility of applying CVM to value forest fire prevention in a developing country, Vietnam. We adopt the US fire reduction survey to the Vietnamese context and implement a pilot survey to illustrate how CVM might be applied to address this issue in a developing country.

2. PROBLEM STATEMENT

One of many functions of any government is the provision of public goods. A public good is often defined as a good with non-rivalry, non-excludability and non-rejectability. The consumption of public goods is non-rival meaning that marginal cost of allowing another person to consume that good is zero. With non-excludability, it is too costly or infeasible to exclude non-payers, and a good is non-rejectable when everyone does consume it whether they want it or not.

The prescribed burning and mechanical fire fuel reduction programs on public lands have characteristics of public goods. Non-rival characteristics of these programs ensure that the safety benefits of one person do not preclude the safety benefits of others.

From non-excludability aspect, once these programs are implemented, the threats from wildfire are reduced; no one can be excluded from the benefits. However, for the prescribed burning and mechanical fire reduction programs, there are spatial limitations to derived benefits creating imperfection in pure public good aspects (Bair, 2001).

One problem with private provision of any public good is free riding behavior of nonpaying beneficiaries. This could prevent economically optimal amount of the public goods from being provided. Free riding in fire risk reduction programs is possible as well. Because of nature of public goods and service of wildfire reduction programs, there is an incentive to privately under-produce the service (Bair, 2001). The characteristics of public goods may lead to lack of profit incentive of private provision then with low effectiveness of investment of projects supplying public goods. Moreover, public goods or their service are not traded in the market and are supplied mainly through government provision, therefore lack of price and quantity signal can often be seen. The value of the service at a specific quantity is not directly observable. That is why preference for various level of wildfire risk reduction implementation is difficult to determine (Bair, 2001).

With the characteristics of public goods, the value of prescribed burning and mechanical fire fuel reduction programs on public lands can be determined by using non-market valuation methods. These methods include revealed preference and stated preference approaches. The willingness to pay for fire risk reduction programs could be reflected based on expected losses of housing property, differences in taxes among different areas, or on difference of prices of houses. This could be done through use of indirect approaches such as hedonic property method. The direct approach including contingent valuation method involves surveys to elicit how much people would pay for hypothetical changes in some environmental resources (Smith, 1993). Using the survey techniques, the value of prescribed burning and mechanical fire fuel reduction programs is elicited and the demand for wild fire reduction services is determined allowing for a more accurate representation of the benefits and costs from which resource managers may make decisions for program implementation.

California, Florida and Montana are located in the West Coast, East Coast and Northern Rocky Mountains, respectively of the United State of America (US). Among these states there exist many different features including racial composition, languages, income levels, geographic differences and of course the level of wild fires. The residents in these three states may view wild fire reduction programs differently leading to the fact that they value these programs also differently. The Divisions of Forestry of three states provide information to the residents about wild fire reduction programs. As mentioned above, these programs have characteristics of public goods and there are no market signals from which preferences are directly observable, even though people receive benefits from the service of these programs. Public acceptance or knowledge on wild fire risk reduction programs is very important for successful implementation. Thus, one of the crucial tasks of the state forestry divisions in California, Florida and Montana states and the U.S. Forest Service that manages surrounding National Forests is to specify groups within the population that may encourage implementation or need further education on these programs. People in different states may act differently and have different perceptions of fire risk reduction programs. There are not available sources of information or signals that reveal the demand of the service of these programs and what attributes dictate the preference of the programs in three states. Uncovering this type of information would allow the program managers, program implementers and policy makers to determine the concerns of people in three states in supporting prescribed burning and mechanical fire fuel reduction. Besides that how well the contingent valuation method works in different states of the US and among different groups of people would be tested in order to determine applicability of the method. If the difference in application towards CVM is found among California, Florida and Montana, then this may suggest the need to tailor the CVM surveys in the future for specific states. This is an important factor contributing to successful implementation of fire risk reduction programs in particular and contingent valuation surveys as whole, and for determining if national fire policies must be tailored or adjusted to individual states.

3. OBJECTIVES OF THE STUDY

The first objective of the study is to determine if differences exist in CVM survey response rates for white people and Hispanic people in California, Florida and Montana on two programs: prescribed burning and mechanical fire fuel reduction. With the null hypotheses of no difference of response rates among these groups of people on two programs, we expect to see that white people and Hispanic people react differently to two programs in three states.

The second objective is to compare the protest refusal to pay responses of white people in California, Florida and Montana and Hispanic people in two states California and Florida. Here we would like to find out the reasons people place a zero value on two programs. Knowing this information is important to policy makers and to program managers.

The third objective is to find out whether willingness to pay of white and Hispanic people in three states for the two programs is affected by geographic difference or not.

The fourth objective is to test the impact of the magnitudes of acreage reduction of wildfires on probability to answering yes to bid amount for two programs in three states. If the acreage reduction variable is significant, a marginal value per acre and per house will be calculated.

The last objective of the study is to see how the CVM would work in Vietnamese context using a small sample of respondents for forest fire prevention program. With this survey, we would try to gather some lessons for conducting a CVM in a developing country, particularly in Vietnam.

CHAPTER II: LITERATURE REVIEW

1. CONTINGENT VALUATION METHOD STUDIES ON POLICIES FOR ENVIRONMENT AND NATURAL RESOURCES

The forest provides many benefits to our society. It supplies input materials for wood processing industry. In addition to this, the forest gives us aesthetic and recreational opportunities. These are considered use values. It also provides an ecosystem for plants and animals to live and thrive in. If these plants and animals are not regularly viewed by people, then these are considered passive use or existence values to the general public who may never visit the forest. Economic value of commodities such as timber can be measured by market prices but many recreational and passive use values cannot be determined by the price mechanism. For example, market prices do not exist for aesthetic value of forests. As mentioned in the previous parts, fire fuel treatment programs on public lands have characteristics of public goods, therefore they can not be purchased in a market. Thus, we do not observe a market price on public forests protected by these programs.

To estimate the value of these public goods, a non-market valuation technique should be used. One of these techniques is the contingent valuation method in which willingness to pay of the respondent to fire fuel treatment programs could be elicited.

Contingent valuation method belongs to stated preference approach that can be used to provide measures of the economic value of natural resource preservation programs (Bateman *et al.*, 2002). The basic idea of this method is to ask interviewees how much they value a contingent change of a natural resource. Up to now there are many studies using CVM. The contingent valuation method was first used by Davis (1963) to estimate the value of big game hunting in Maine. After that some of the first applications were used by Randall *et al.*, (1974). With regard to application of CVM to forest protection see Hagen *et al.*, (1992), Loomis and Gonzales- Caban (1998), Loomis *et al.*, (2002), Loomis *et al.*,(2003), and Champ *el at.*,(2002), to name just a few.

One of important steps in CVM is to design a hypothetical market for a good or service that is not normally allocated via the market. We can use different willingness to pay question formats for such a hypothetical market. These are open-ended or dichotomous choice WTP question formats. The later got much attention of researchers in the last decade and has been recommended by the US Department of Commerce's National Academic and Atmospheric Administration (NOAA) (Arrow *et al.*, 1993). Bateman *et al.*, believed that referendum method became increasingly popular in the 1990s. The elicitation format is thought to simplify the cognitive task faced by respondents. This question format is superior to other donation types of formats in a contingent setting (Champ *et al.*, 2002). This format creates a voter like scenario that most respondents are familiar with from elections. It asks respondents to vote for or against a change to a natural resource if the change were on the next ballot. This procedure minimizes non-response and avoids outliers (Bateman *et al.*, 2002).

In the case the respondent votes against the program or a change to a natural resource, we can use the follow-up questions to find out why they voted against the program. From these questions we can evaluate whether respondents held some values for the program or protest the program completely (Halsted *et al.*, 1992).

Loomis and Gonzales-Caban in 1998 carried out a study on protecting Oregon's forest from fires. They use dichotomous choice referendum question format to elicit respondents' willingness to pay for a fire prevention program in California and Oregon. The survey also included residents of New England states. Benefits of this program were estimated by probit regression and these estimates were evaluated as the proportion of households that responded to the survey and at the aggregated level for the entire United States. These researchers found that benefits exceeded the cost of implementing the fire management in California and Oregon to protect spotted owls and contingent valuation method is a useful tool in valuing public land fire decisions. While examining the fire prevention, Loomis and Gonzales-Caban did not take into account the different backgrounds of the respondent and did not provide the conclusion on applicability of this approach in other states of USA.

Hagen *et al.*, (1992) used dichotomous referendum question in determining benefits of preserving old growth forest and spotted owls. They examined whether a conservation policy or pre-existing timber plan is more valuable. WTP for adoption of the conservation policy was elicited. The binominal logit model was used to measure the benefits to the surveyed households. The finding of the research supports implementation of the policy. The survey was carried out nationwide, so the benefits may be overestimated and the costs related to the policy implementation could be less that the costs calculated for specific forests or a region where forests are located.

2. STUDIES RELATING TO DIFFERENCES IN LANGUAGES AND ETHNICITIES IN CONTINGENT VALUATION SURVEY

Executive Order 12898 by President Clinton requires federal agencies to evaluate environmental justice of federal actions on minority population (Loomis *et al.*, 2002). According to this Executive Order, policy makers have to take into account the impact of their projects, policies on different cultures in the United States. Surveys such as CVM are one means that agencies often use to assess potential effects of some programs on households. However, past household surveys were implemented mainly in English and thus excluded about 18% of the US population (Ellingson, 2003). In order to fully evaluate the impact of natural resources on our society, other languages such Spanish, and different ethnic groups of people need to be utilized in the data collection process.

Loomis, Bair and Gonzales-Caban (2002) examined language related differences in a contingent valuation study for English and Spanish speaking people for two programs: prescribed burning and mechanical fire fuel reduction in Florida. First, they examined the response rate in the survey carried out in English and Spanish. The similar response rates have been found among Spanish and English speaking households. However, there were significant differences in the most frequent reasons given for refusing to pay (Loomis *et al.*, 2002). The pooled logit model was used to figure out the impact of language on response rate. The study found that language intercept and bid interaction variables were insignificant in both programs. In addition, these researchers also did not find any statistical differences between languages in the mean WTP for either fire fuel treatment program. Two things that Loomis, Bair and Gonzales-Caban did not include in their study are potential response differences by ethnicity and geographic difference effect on WTP. Spanish speaking households in Florida may have different response rate than those Spanish-speaking households in California because Spanish-speaking people in Florida came mainly from Latin America and Cuba, while in California they have Mexican descent. In our study, we will focus on state interaction effect on response rate in CVM survey.

To evaluate influence of different languages and ethnicities in CVM surveys, Loomis *et al.,* (2004) compared the response rate from several ethnic groups of people from two programs: prescribed burning and mechanical fire fuel reduction in California. In their study, the whites, African Americans and half of Hispanics received the survey in English, the other half of Hispanic sample received the survey in Spanish. They found that there were significant differences in interview response rate of the whites, African Americans and Hispanics. The mean WTP across ethnic groups was found not to be significantly different for both programs. Another interesting finding is that different ethnic groups responded differently to the two programs but substantial support and WTP by the whites and African Americans for prescribed burning and for the whites and Hispanics for mechanical fire fuel reduction in California. One of objectives of our study is to examine reaction of the same ethnic group of people in different states of USA to two programs. This also allows us to see applicability of CVM across country.

With the same purpose of the previous study, Loomis, Gonzales- Caban and Hesseln carried out a study in Montana for its residents and members of two Native American tribes. They arrived at the conclusion that the survey response rate of Native Americans and other Montana's residents was similar on the initial phone interview, but fell significantly for Native Americans for the follow-up in depth interviews. The protest rate between the two groups of people for prescribed burning is not significantly different but significantly different for mechanical fire fuel reduction at 0.05 level. Using overlapping confidence intervals, these authors found that there is no statistical difference between population groups' WTP for both fire fuel treatments programs.

CHAPTER III: THEORETICAL FRAMEWORK

1. STATISTICAL MODEL SPECIFICATION

Contingent valuation method is a direct valuation approach where respondents express directly their preferences, in money terms, for a hypothetical change of natural resources or environment to be delivered by a proposed policy action. It is believed that individuals transform these preferences into money value. From a welfare theoretic point of view, the contingent valuation methodology denotes a set of procedures used to generate, through direct questioning, estimates of the measures of welfare changes (Nunes, 2000). In the dichotomous choice WTP question format, the willingness to pay of respondents for a change of natural resources by a proposed policy action is not known with certainty to the researcher, therefore the researcher uses the respondent's "no" or "yes" responses to the bid elicitation as an indicator of the range of WTP. This valuation scheme has been proposed originally by Bishop and Heberlein, and later explored by Michael Hanemann and Trudy Cameron (Nunes, 2000).

1.1. Bishop and Heberlein (1979) approach

These researchers used the "yes-no" answers from respondents upon each bid amount and calculate the proportion of yes answer to each bid b_k based on the following formula:

$$Ln(\frac{\pi}{1-\pi}) = \alpha + \beta \ln(b_k) + \varepsilon_k$$

Where π is a proportion of yes to bid b_k, ε_k is an error term. Here we expect $\beta<0$ because when b_k increases fewer people say yes to the bid.

1.2 W. Michael Hanemann's (1984) approach

Suppose P_1= Pr(willing to pay)= $Pr\{(V(1,y-b,q_1)+\varepsilon_1> V(0,y,q_o)+\varepsilon_0\}$, where Pr is probability, V is indirect utility of respondent, 1 is when respondent agrees to pay, 0 is when respondent does not agree to pay, y is income of respondent, b is bid amount the respondent is asked to pay, q_1 is the state of environment or natural resources with a proposed policy action and q_0 is the state of environment or natural resources without a proposed policy action.

$P_1= F_\eta(\Delta V)$ where $\Delta V= V(1, y\text{-}b, q_1)- V(0, y, q_0)$, F_η is distributional prior.

P_1= Pr (E>b) = 1- $G_{WTP}(b)$, where E is maximum WTP, and $G_{WTP}(b)$ is the cumulative distribution function of WTP. From here we could determine that

P_0= Pr (refuse to pay) = 1-P_1= G_{WTP} (b).

From this distribution, the mean and median WTP of the sample can be calculated. This distribution of the utility difference can be either normal leading to a probit model or logistic leading a logit model.

1.3. Empirical logit model of willingness to pay

In a study on hunters' willingness to sell and willingness to pay for obtaining hunting permits, Mitchell Hanemann (1984) used logit model for contingent valuation experiment with discrete responses. Since then, many papers have used logit models to evaluate CVM dichotomous choice results. This includes Loomis *et al*, (1987), Loomis *et al.*, (1998), Loomis *et al.*, (2002), Loomis *et al.*, (2003., Haab and Mcconnell (1998), Hagen *et al.*, (1992). Why is the logit model used in dichotomous response study?.

According to Hanemann (1984), respondents evaluate the utility difference associated with the current program level versus paying some amount of money ($X) for an increase in the program level. If the utility difference is positive for the program, the individual is believed to respond “yes”. The utility difference can be distributed logistically or normally. The logit model is less computationally difficult to estimate and often gives results similar to the normal distribution. Gujarati, (1997) provides three reasons why a logit model is used instead of ordinary least square OLS. *First*, with a qualitative dependent variable, data is non-linear. The dependent variable takes on a value of one or zero. Zero for a no vote and one for a yes vote. *Second*, the ordinary least square estimates are not efficient since the estimators do not exhibit the minimum variance and the error term is heteroscadastic. Also, with OLS the predicted probabilities can be greater than one and less than 0. To avoid these problems in the processing data, the logit regression can be used. The logit regression follows the logistic distribution.

The binominal logit is an estimation technique for equation with a qualitative dependent variable. The dependent variable is log odds ratio of probability that the choice will be made with (Gujarati, 1997). Cumulative logistic distribution function is:

Pi= $\frac{1}{1+e^{-Zi}}$ Where Pi is probability of yes to vote for the program,

Zi= $e^{-(\beta_1+\beta_2\chi_i)}$, Xi is the monetary amount of bid respondent is asked to pay. Then 1-Pi is the probability of no vote for the program. And 1-Pi= $\frac{1}{1+e^{Zi}}$.

$\frac{Pi}{1-Pi} = e^{Zi}$; $\frac{Pi}{1-Pi}$ is simply the odds ratio in favor of voting for the program.

By taking the log of the odds ratio, we would have:

$$Li = Ln\left(\frac{Pi}{1-Pi}\right) = Zi = \beta_1 + \beta_2 Xi.$$

L -the log of the odds ratio is not only linear in X but also linear in the parameters and this is the logit model.

Model construction

* Choice of variables for econometric analysis.

The dependent variables in our models are votes for bid amounts for implementation of prescribed burning and mechanical fire fuel reduction programs. One is vote for and 0 is against these programs given a bid amount.

To reduce multicolinearity among independent variables, we started with independent variables that have been used to evaluate these two programs in separate analyses conducted for California, for Florida and for Montana. The first paper is on the influence of ethnicity and language on economic benefits of forest fire prevention from prescribed burning and mechanical reduction methods in California (Loomis John *et al*, 2004). The second paper illustrated the language-related difference in a contingent valuation study: English versus Spanish in Florida (Loomis John, Luca Bair and Armando Gonzales-Caban, 2002). The third one is on estimating the public's willingness to pay for prescribed burning and mechanical fuels reduction: a comparison of Native American and Montana residents (Armando Gonzales-Caban, John Loomis, and Hayely Hesseln, 2002). These variables are described in table 3-1.

The empirical logit models for two fire fuels reduction programs:

The logit model for prescribed burning:

$$(1)\ Ln\left(\frac{Pi}{1-Pi}\right) = \beta_0 + \beta_1\, RXBid + \beta_2 FL + \beta_3 FL{*}Bid + \beta_4 CA + \beta_5 CA{*}RXBid + \beta_6 X_6 + \ldots\ldots + \beta_n X_n + u_i$$

The logit model for mechanical fire fuel reduction program:

$$(2)\quad Ln(\frac{Pi}{1-Pi}) = \beta_0 + \beta_1\,\text{MechBid} + \beta_2\text{FL} + \beta_3\text{FL*MechBid} + \beta_4\text{CA} + \beta_5\text{CA*Bid} + \beta_6 X_6 + \ldots\ldots + \beta_n X_n + u_i$$

In our study, the respondent was asked for opinions on two programs: prescribed burning and mechanical fire fuel reduction. Therefore, the disturbances of two above logit models are correlated to each other with zero expected values, unit variances and ρ covariance. According to Green (2000), bivariate logit model could be used instead of single models 1 and 2. Using the bivariate logit model has several advantages: it is computationally simpler, and odds ratios are preferred to correlation coefficients when describing the association between two binary variables.

Each model is run with 2 options: Income included and income excluded due to high item non-response on the income question. It is clear that some people feel that income is too personal, therefore they do not want to reveal their income. So, if income is included in the regression then the number of omitted observations is greater than that with income excluded. The purposes of including income in the model are: To see whether income could affect the explanatory power of the logit models and to find out how people in three states choose the optimal amount of prescribed burning and mechanical fire fuel reduction goods to consume basing on budget constraint (income) and preference (indifference curve).

For each of two options, the model is to be examined with protest responses included and excluded for comparison and contrast. From the results of regressions, the difference between people who agree with and who disagree with two fuels reduction programs could be identified.

To calculate WTP, the original model is run only with significant variables. Doing this minimizes the variance around estimated WTP since including insignificant variables increases the variance around the logit coefficients.

2. SOME BASIC ISSUES OF CVM RESPONSES

2.1. Are statements of hypothetical WTP credible?

As far as responses to a contingent valuation questionnaire are concerned, according to Mitchell and Carson (1989), the basic issue is whether the necessarily hypothetical character of contingent valuation automatically renders their findings meaningless. Carson *et al.*, (1999) examined this issue by looking at whether survey respondents would consider questions of some wider consequence or not. A question will be considered consequential if and only if:

1. The residents feel that their response may influence the actions of relevant agencies and,
2. The respondents care about the outcome.

If two conditions hold then the question will be consequential. If either of the conditions does not hold, then the respondent is believed to consider the question to be no consequence and any response has the same influence on his or her utility. Expectations from consequential questions can be as follows:

- Respondents will answer so as to maximize their expected wellbeing, therefore they will respond to the incentive as set out in the survey design, or
- Respondents will answer truthfully irrespective of the above.

2.2. Concerns regarding survey response rates

The survey response rate depends on many factors. Contingent valuation mail surveys have experienced considerably lower response rate than other types of survey (Mitchell and Carson, 1989). Boyle believes that personal interview has the highest respondent cooperation in the two components dealing with the overall response rate to the survey and item non-response to individual questions in returned survey. This problem also influences sample selection effects. Young black or unmarried people who live alone in large cities and work are hard to be found at home, therefore they are less available at home (Champ, Boyle, and Brown, 2003).

There have some studies comparing different data collection modes. Either *et al.* in 2000 compared phone and mail contingent value responses for green pricing electricity programs, Loomis and King (1994) focused on differences of mail and telephone-mail contingent valuation survey, meanwhile Mannesto and Loomis (1991) evaluated mail and in person contingent valuation surveys. The questions these researchers tried to answer are 1) Are the response rates the same across modes?, 2) Do the same type of people respond to each mode?, 3) Do the different modes result in differing levels of item non-response to the contingent valuation questions?, 4) Is it possible to develop identical sample frames?, 5) Are welfare estimates affected by the survey modes? (Champ, Boyle, and Brown, 2003). The important general finding from these studies is that survey modes do affect estimates of values.

The design of survey also has impact on response rate. Cummings *et al.,* thought a careful designed questionnaire with well-written questions would have higher response rates in mail surveys. Sometimes, sponsors or agencies doing the research could have certain influences on response rate. The survey implemented by the US Department of Agriculture may have higher response rate that the survey from some universities. Interviewers from some research center could have more response answers than graduate students do.

How to calculate the response rate depends on data collection modes. The correct way to calculate the response rate for mail survey is to divide the number of completed questionnaires returned by the number in the original sample (Mitchell and Carson, 1989). Basically, response rate RR= $\frac{RN}{ON}$ *100%, where RN is the returned completed questionnaires and ON- the original number of sample. However, most researchers deduct from the original number on the sample the number of people who have moved out of the sample area, decreased people and others that are ineligible for the sample frame. No matter what data collection modes are used and who sponsor the studies, who do the interview, some level of non-response to the willingness to pay is virtually inevitable. This means that the response rate is always less that 100%.

Mitchell and Carson have put non-response into two groups. In the first, known as unit response, the person (household) fails to respond to the questionnaire because people can't be found at home by phone or in-person interview or then those sampled in a mail survey fail to return the questionnaire. The second group called item non-response, a respondent answers some or most of the questions on a survey but fails to answer a particular question of interest such as willingness to pay question. Meanwhile, Bateman *et al.* looked at 3 forms of non-response:

How much percent of response rate is good and acceptable for a contingent valuation survey?. So far, there is no answer for this question. However, Mitchell and

Carson (1989) believed that in contingent valuation survey, the non-responses rates of 20-30% for WTP elicitation question are not uncommon where sample is random and includes people of different educational and age levels, the scenario is complicated... On the other hand, we could expect 95% of response rate in the survey where people know well the amenity and benefit from the outcome of the research.

3. PROTEST RESPONSE

In continent valuation surveys, we often see a small percentage of respondents who refuse to take the CVM scenario seriously. Respondents who give a zero valuation or refusal to pay, not because they do not value the good or they can not afford to pay, but because they reject the scenario or rationale that citizens should have to pay for this program are often termed protest responses (Loomis, Bair, Gonzales-Cuban, 2002). Thus, it is important to distinguish true zero valuations and protest responses. According to Loomis and Walsh (1997), questions to identify protesting the program (against hypothetical market, payment method...) should be included in the questionnaire. For example:

Did you answer zero because of (check one)

1. It is not reasonable to expect you to pay for this program.
2. You do not think this program would work at all.
3. You do not believe that collected money be spent as it is supposed to be.
4. You do not want to pay because you believe others will not pay.
5. You think that method of payment is not fair and trustful.

This kind of answers should be omitted from the calculation of average willingness to pay for the sample of respondents (Loomis and Walsh, 1997). Some people believed that the survey with more than 15 % protest response rates should not be used in decision asking because high incidence of protest may indicate that other values may also distorted (U.S. Water Resource Council, 1983).

Table 3-1 Explanation of variable for econometric models

Variables	Variable explanation
VoteRXPr	Dummy variable: 1 if respondent votes for prescribed burning program, 0 otherwise
VoteMechPr	Dummy variable: 1 if respondent votes for mechanical fire fuel reduction program, 0 otherwise
Age	Age of the respondent in years
CA	Dummy variable: 1 for California state, otherwise is 0
FL	Dummy variable: 1 for Florida state, otherwise is 0
Educ	Education level of the respondent in years
Expsmoke	Dummy variable: 1 if the respondent experienced smoke from a wildfire or prescribed burning or mechanical fuels reduction program, 0 otherwise
Income	Household income of the respondent
MechBid	Bid amount for mechanical fire fuel reduction program
Ownhome	Dummy variable: 1 if respondent owns a home, 0 of respondent rents
Respprob	Dummy variable: 1 if respondent suffers from respiratory or breathing problems, 0 otherwise
RXBid	Bid amount for prescribed burning program
Witnessfire	Dummy variable: 1 if respondent witnesses a wild fire, 0 otherwise
CA-RXBid	Interaction term: CA*RXBid- The effect of bid amount in CA on probability to vote for RX program
FL-RXBid	Interaction term: FL*RXBid- The effect of bid amount in FL on probability to vote for RX program
CA-MechBid	Interaction term: CA*MechBid- The effect of bid amount in CA on probability to vote for Mech program
FL-MechBid	Interaction term: FL*MechBid The effect of bid amount in FL on probability to vote for Mech program

CHAPTER IV: HYPOTHESES INVESTIGATED

I. HYPOTHESES FOR TESTS ON RESPONSE RATE

Up to now, there have been no published papers comparing CVM response rate of the similar groups of people living in different states of USA. We might expect differences in responses to the CVM survey across geographic areas of different states. This could arise as a differential reaction to one of several aspects in a CVM survey: 1) a scenario description of a problem, 2) the proposed solutions, 3) an associated vehicle to pay for the solution (Loomis, Bair and Gonzales Caban, 2002). In addition there may be different responses to how the survey is administered. However in our study all three surveys in California, Florida and Montana were implemented through an identical phone-mail-phone method and as follows:

1) Initial random digit dialing phone call with a short interview (5 minutes) initial interview. The purpose of this is to introduce study aims, have the name and address to send a survey booklet and schedule a time for an in-depth (20 minutes) interview.
2) Color booklet containing questions, picture describing 2 prescribed burning and mechanical fire fuel reduction programs are sent to people who provided their addresses.
3) In depth phone interviews with respondents using booklet as a visual aid.

The interviewers identified themselves as being with a California university in the California and Montana studies. In the Florida we used the university of Georgia survey research center. Therefore it is hypothesized that white people and Hispanic people in three states may have different response to taking a survey. White people are more likely to be college educated and have a positive view of universities. Such a differential response rate between whites and Hispanics could make the survey more difficult to generalize resulting economic values from the survey sample to the population (Loomis, Ellingson, Gonzales-Caban, 2003). With phone-mail-phone survey described above, we could compare response rate that include those people participated in the first and second interviews. The null hypothesis is that overall survey response rate (RR) to the CVM survey is independent of state interaction effects:

1) $H_0: RR^{CA}_{White} = RR^{FL}_{White} = RR^{MT}_{White}$

2) $H_0: RR^{CA}_{Hispanic} = RR^{FL}_{Hispnaic}$

Where CA stands for California, FL- Florida and Montana- MT.

We use χ^2 test for two cases of initial and in-depth interviews.

2. HYPOTHESES FOR TESTS ON PROTEST RESPONSE

As mentioned above, the values of prescribed burning and mechanical fire fuel reduction are not directly observable in the market. Therefore, people in different states may view these programs in different aspects. Responses to the WTP questions during the in-depth interview are the main focus of our analysis. Some refusals to pay are valid expression of zero WTP since they reflect lack of value for the good or low income (i.e, inability to pay) (Loomis, Ellingson, Gonzales-Caban, 2003). The null hypothesis is that differences in protest and non-protest responses (PR) are the same among white people and Hispanic people in three states California, Florida and Montana for the prescribed burning and mechanical fire fuel reduction programs.

1) Prescribed burning program

H$_0$: $PR^{CA}_{White} = PR^{FL}_{White} = PR^{MT}_{White}$

H$_0$: $PR^{CA}_{Hispanic} = PR^{FL}_{Hispnaic}$

2) Mechanical fire fuel reduction program

H$_0$: $PR^{CA}_{White} = PR^{FL}_{White} = PR^{MT}_{White}$

H$_0$: $PR^{CA}_{Hispanic} = PR^{FL}_{Hispnaic}$

The test of significance will be performed using a χ^2 test.

3. HYPOTHESES FOR TESTS ON GEOGRAPHIC DIFFERENCE EFFECT ON WILLINGNESS TO PAY

The effect of states can be tested using a logit model in two primary ways. First we can test whether state simply shifts the logit index function up or down, by some amount β_2 and β_4 or rotates the logit index by β_3 and β_5 in the equation 1 and 2 below for each program with subsuming Montana as the base case.

Prescribed burning program:

$$(1)\ \mathrm{Ln}\left(\frac{Pi}{1-Pi}\right) = \beta_0 + \beta_1\,\mathrm{Bid} + \beta_2\mathrm{FL} + \beta_3\mathrm{FL}*\mathrm{Bid} + \beta_4\mathrm{CA} + \beta_5\mathrm{CA}*\mathrm{Bid}$$

$$+\beta_6 X_6 + \ldots\ldots + \beta_n X_n + u_i$$

Mechanical fire fuel reduction program:

$$(2)\qquad (2)\ \mathrm{Ln}\left(\frac{Pi}{1-Pi}\right) = \beta_0 + \beta_1\,\mathrm{Bid} + \beta_2\mathrm{FL} + \beta_3\mathrm{FL}*\mathrm{Bid} + \beta_4\mathrm{CA} + \beta_5\mathrm{CA}*\mathrm{Bid}$$

$$+\beta_6 X_6 + \ldots\ldots + \beta_n X_n + u_i$$

Where Bid- the dollar amount of bid the respondent is asked to pay; FL – Florida, CA- California, are shift variables and they equal 1 for states of Florida and California, respectively and 0 otherwise, FL*Bid, CA*Bid are interaction terms, u_i is the stochastic disturbance term with normal distribution with zero mean (Gujarati, 1997). We will estimate each model twice- one for the whites in CA, FL and MT, and one for Hispanics in CA and FL.

Then the null hypotheses are:

Ho: $\beta_2 = 0$
$\beta_3 = 0$
$\beta_4 = 0$
$\beta_5 = 0$

The hypotheses are tested using t- statistic on β_2, β_3, β_4, β_5.

A more general test is to evaluate whether all coefficients in the equation 1 and 2 vary with states. To test this, we estimate logit models for white people in three states California, Florida and Montana and logit models for Hispanic people in two states California and Florida for each program.

For prescribed burning program

White people in California, $\text{Ln}\left(\frac{Pi}{1-Pi}\right) = \alpha_0 + \alpha_1\,\text{Bid} + \alpha_2 X2 + \alpha_3 X3 + \ldots\, \alpha_n Xn + u_j$

White people in Florida, $\text{Ln}\left(\frac{Pi}{1-Pi}\right) = \gamma_0 + \gamma_1\,\text{Bid} + \gamma_2 X2 + \gamma_3 X3 + \ldots\, \gamma_n Xn + u_k$

White people in Montana, $\text{Ln}\left(\frac{Pi}{1-Pi}\right) = \delta_0 + \delta_1\,\text{Bid} + \delta_2 X2 + \delta_3 X3 + \ldots\, \delta_n Xn + u_l$

Hispanic people in California, $\text{Ln}\left(\frac{Pi}{1-Pi}\right) = \lambda_0 + \lambda_1\,\text{Bid} + \lambda_2 X2 + \lambda_3 X3 + ..\lambda_n Xn + u_n$

Hispanic people in Florida, $\text{Ln}\left(\frac{Pi}{1-Pi}\right) = \mu_0 + \mu_1\,\text{Bid} + \mu_2 X2 + \mu_3 X3 + ..\mu_n Xn + u_m$

The null hypotheses:

Ho: $\alpha_0 = \gamma_0 = \delta_0;\ \alpha_1 = \gamma_1 = \delta_1;\ \alpha_3 = \gamma_3 = \delta_3;\ \ldots\ldots\ \alpha_n = \gamma_n = \delta_n$ (White people)

Ho: $\lambda_0 = \mu_0;\ \lambda_1 = \mu_1;\ \lambda_2 = \mu_2;\ldots\ldots;\ \lambda_n = \mu_n$; (Hispanic people)

We can use likelihood ratio test on these separate equations for the program.

We do the same for mechanical fire fuel reduction program.

To test the state effects on willingness to pay, we compare WTP of each group of people across three states for each program. The null hypotheses state that WTP of California's white people are the same as that of Florida's white people and Montana's white people.

Ho: $WTP_{CA}^{White} = WTP_{FL}^{White} = WTP_{MT}^{White}$;

Ho: $WTP_{CA}^{Hispanic} = WTP_{FL}^{Hispanic}$.

After this step we can calculate the willingness to pay for each group of people using the formula proposed by Hanemman in 1989 as follows:

Mean $WTP_{CA}^{White} = \ln(1+\exp(\alpha_0 + \alpha_2 X2 + \alpha_3 X3 + \ldots \alpha_n Xn))/ABS(\alpha_1)$ for white people in California and using respective logit model coefficients, we can do for other groups and other states (ABS- absolute value).

Then we would have $WTP_{CA}^{White}, WTP_{FL}^{White}, WTP_{MT}^{White}, WTP_{CA}^{Hispanic}, WTP_{FL}^{Hispanic}$ calculated.

Median WTP = $(\alpha_0 + \alpha_2 X2 + \alpha_3 X3 + \ldots \alpha_n Xn)/\ ABS\ (\alpha_1)$

The null hypotheses would be tested by whether the confidence intervals overlap (Park, Loomis and Creel, 1991).

4. HYPOTHESES FOR SCOPE TEST OF REDUCTION OF ACREAGE BURNED

4.1 Concept of scope test

Contingent valuation method is direct method where any biases on the part of interviewers, the design and implementation of the survey, the respondent can jeopardize the reliability and validity the CV survey (Mitchel and Carson, 1989). Therefore, reducing biases is one of solutions to increase the reliability of CV. One way the validity is mainly assessed is from the answer to a question: How does the WTP vary with factors that could logically be expected to influence it under an economic theory? (Mustaq and Shunji, 2002). One of the logical checks is that the WTP showed increase when more of the "good" is offered. This is usually termed a scope effect or scope sensitivity analysis. Scope sensitivity is considered a necessary condition for the validity of the WTP. Thus, the scope test, to measure the sensitivity of the WTP in accordance with the change in levels or amount of the public goods offered, has attracted much attention and it has been regarded as the acid test for a CV study (Mustaq and Shunji, 2002). The scope test could be internal and external. The internal scope test is to measure the change in WTP for different levels of the good for the same respondent, whereas the external test measures the change in WTP for separate respondents at different levels of the public good. For external analysis, we can compare the WTP estimates from different people who were given a CV scenario with a different level of the reduction in acres of forest fires.

4.2 Scope sensitivity analysis for prescribed burning and mechanical fire fuel reduction programs

In our study for fire fuels reduction programs, we carry out scope test on the impact of a reduction in acreage of forest fires on the WTP. Here, in accordance with the criteria and theory, we believe that this acreage reduction variable should be significant and the sign of coefficient is positive meaning that the more acreage is reduced the more people would be willing to pay more. We are able to conduct an external scope test because the amount of acreage reduction varies across the three states of CA, FL and MT.

Step 1: Establishment of the logit model for scope test:

The logit models for prescribed burning and mechanical fire fuel reduction programs are:

The prescribed burning program:

$$(1)\ \mathrm{Ln}\left(\frac{Pi}{1-Pi}\right) = \beta_0 + \beta_1 \mathrm{Acrereduction} + \beta_2\ \mathrm{RXBid} + \beta_3\ X_3 + \ldots\ldots + \beta_n X_n + u_i$$

Mechanical fire fuel reduction program:

$$(2)\ \mathrm{Ln}\left(\frac{Pi}{1-Pi}\right) = \beta_0 + \beta_1 \mathrm{Acrereduction} + \beta_2\ \mathrm{MechBid} + \beta_6 X_6 + \ldots\ldots + \beta_n X_n + u_i$$

Table 4-1 Independent variables in scope test model

Variables	Variable explanation
VoteRXPr	Dummy variable: 1 if respondent votes for prescribed burning program, 0 otherwise
VoteMechPr	Dummy variable: 1 if respondent votes for mechanical fire fuel reduction program, 0 otherwise
Acrereduction	Acreage of burned forest reduction
Age	Age of the respondent
Educ	Education level of the respondent
Expsmoke	Dummy variable: 1 if the respondent experienced smoke from a wildfire or prescribed burning or mechanical fuels reduction program, 0 otherwise
Income	Household income of the respondent
MechBid	Bid amount for mechanical fire fuel reduction program
Ownhome	Dummy variable: 1 if respondent owns a home, 0 of respondent rents
Respprob	Dummy variable: 1 if respondent suffers from respiratory or breathing problems, 0 otherwise
RXBid	Bid amount for prescribed burning program
Witnessfire	Dummy variable: 1 if respondent witnesses a wild fire, 0 otherwise

From equations 1 and 2, Hanemann (1989) provides a formula to calculate the mean WTP for the individual. The formula is:

Mean WTP_{CA}^{White} = ln (1+exp ($\beta_0 + \beta_1 X_1 + \beta_3 X_2 + \ldots\ldots + \beta_n X_n$))/ABS (β_2)

Where $X_1, \ldots X_n$ is the average values of independent values.

The more useful thing for fire policy analysis is the marginal WTP as a function of acres of forests that no longer burns (Loomis and Gonzalez-Caban, 1998). We can derive this function as follows:

(3) WTP = ($\beta_0 + \beta_1$ Acrereduction)/ ABS (β_2) where ABS is absolute value. The annual WTP was asked. β_0, β_1 and β_2 are from reduced equations: Ln $(\frac{Pi}{1-Pi}) = \beta_0 +$ β_1Acrereduction+ β_2 RXBid for RX program and Ln $(\frac{Pi}{1-Pi}) = \beta_0 + \beta_1$Acrereduction + β_2 MechBid for mechanical fire fuels reduction program.

Step 2: Hypothesis for scope test:

The scope test involves testing whether the sign of acreage reduction variable is positive or not. Therefore the null hypothesis is:

H_0: $\beta_1 = 0$

Theory suggests the alternative is

H_A: $\beta_1 > 0$.

This is one tailed t- statistic test.

As discussed by Mitchell and Carson (1989), our scope test is to be classified as a test of quantitative nesting. What changes across the survey versions is the change of acreage reduction of burned forests. We believe that people would pay more for more acreage reduction of burned forests and this is true for all three states California, Florida and Montana and for prescribed burning and mechanical fire fuel reduction programs among different groups of people.

CHAPTER V: SURVEY DESIGN AND SURVEY MODE

1. SURVEY DESIGN

The survey design and data relied upon in this and next chapters have come from Loomis, Bair, and Gonzales-Caban (November 2002) and Loomis Gonzales-Caban, and Hesseln (July 2004).

Development of the survey instrument is an important step in the research process. The survey should provide respondents with an informative, accurate and description o the program to elicit an as close as possible representation of the value they place on increased fuel treatment programs. To accomplish this goal, data to develop the survey were collected from mainly three sources: World Wide Web, multitude of agencies and pre tests. World Wide Web becomes a valuable tool in the search for data not only on fuel treatment aspects but also on other necessary information in the research process. The forest protection bureau pages of California, Florida and Montana provide several informative sites. These sites give not only statistics on forest fires in the last decades including analysis of the fire reasons, but also responses of central and local authorities to the fires events, critique and assessments and success of current programs on fire management. Besides this, the Environmental Protection Agencies of these states also post data on air quality such as reports on impacts of fires on environment. The air quality data are available through EPA web sites and these data list air quality level that resulted from different wildfires. The information on air quality levels is gathered through state monitoring stations.

The second information source is the multiple agency reports in wild fires events. These reports are the most comprehensive and complete data reflecting the fire situation in three states and solutions applied when fires occurred. These documents include reports of Federal Emergency Management Agency illustrating and evaluating the fire history of three states California, Florida and Montana, public reaction to fire events and mitigation recommendations. Departments of Forestry in each state have fire event fact sheets that provide detailed information on fire events including evacuation and road closures. The reports from the national inter agency fire center supply information on environmental conditions such as temperature, precipitation, atmospheric events that could lead to fires in the last few years. Other documents give detailed information on current efforts of 3 states in trying to reduce possibilities of fire occurrence like California's fire plan.

The third source of information is pre tests. Pretesting is used to evaluate the survey instrument. To begin pretesting, random individuals are to be contacted and asked to participate in a small survey.

The central part of this kind of survey instrument is to construct a booklet to send to respondents. The first page of the booklet is a brief introduction to the topic of prescribed and wildfire then provide detailed definitions. These definitions include prescribed burn, wildfire, fire management, structural fire and health standard. (Appendix 1). The definition of prescribed burn is as follows:

A fire purposely set in designated area to accomplish one or more specific objectives such as removal of underbrush and dead wood to reduce available fire fuel and increase the ability to control future wild fires. On this page information on existing prescribed burns conducted by forestry divisions of California, Florida and Montana on federal, state and private forest and rangelands also is provided.

The second page of the booklet contains information on current problems of wildfires in three states and what solutions could ease the problem (Appendix 1). The current problem focused on the fact that over the last decades with the attempt to prevent fires from burning forests and rangelands, unnatural wild fire fuel in the form of bushes, dead branches, logs and pine needles on the forest floor has been built up. The fuels accumulated so significantly that fires no longer burn at natural temperature or rate making them dangerous to fight and difficult to control. Catastrophic fires burn at much higher temperature and can release the energy equivalent of an atomic bomb. The flames from these wildfires burn all the way to the top of tall trees, houses and spread very fast making these wildfires difficult to put out. Under very dry conditions, these high-density wildfires burn nearly everything, frequently causing high level of air pollution. To convey information to respondents, a diagram shown in Figure 1 was developed after several focus groups and pretests in Florida, and was used in all three states. The third page illustrates how these solutions could work. Figure 2 illustrated prescribed burning. The text of the survey stated many advantages of prescribed burning such as lower speed of spreading at 60-120 feet an hour with flames at height of 4-8 feet compared to wildfires spread at speed of ½-2 miles an hour with flames at height of 30-60 feet (Figure

2), possibility of controlling and containing wildfires and protecting houses and other structures that would have been lost.

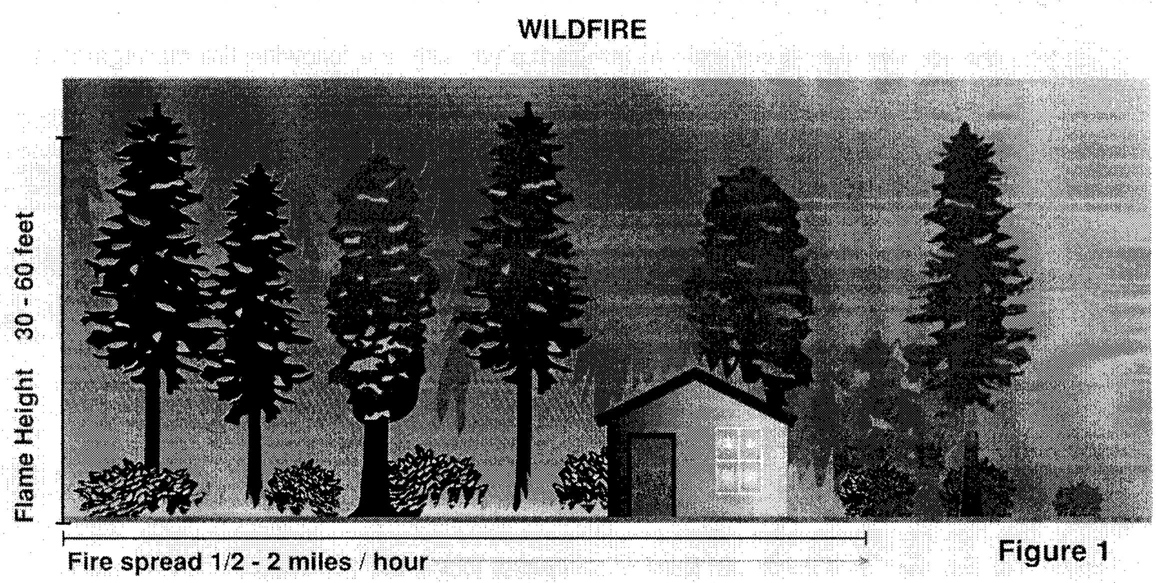


Figure 1

The third page illustrates how these solutions could work. Figure 2 illustrated prescribed burning. The text of the survey stated many advantages of prescribed burning such as lower speed of spreading at 60-120 feet an hour with flames at height of 4-8 feet compared to wildfires spread at speed of ½-2 miles an hour with flames at height of 30-60 feet (Figure 2), possibility of controlling and containing wildfires and protecting houses and other structures that would have been lost. On the other hand, scientific studies also show that with prescribed burning, number of acreage of forests burned by wildfires is reduced each year. In addition, the issue of smoke is also addressed by indicating that while prescribed burning produces smokes, it produces less those wildfires.

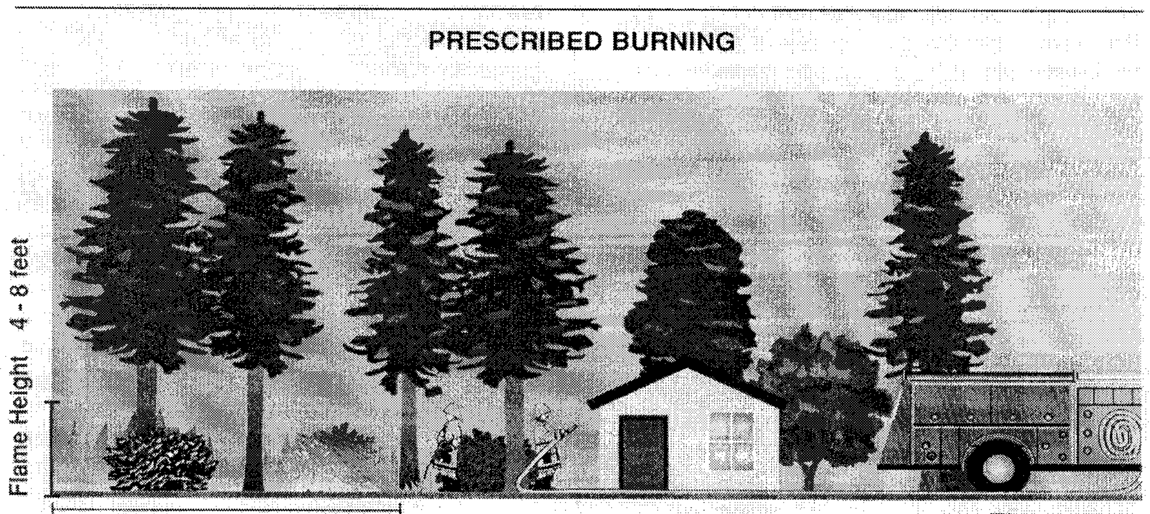


Figure 2

The fourth page of the booklet describes the proposed program and its results in depth (Appendix 1). The proposed program is the extended prescribed burning on 52 million acres, 28 million acres and 30 million acres of federal, state and private forest and rangelands of California, Florida and Montana, respectively. The features of the programs contain the benefits obtained by carrying out this extended prescribed burning including restoring a more natural fire cycle, growth of many types of flowers and shrubs as food sources for wildlife, reduction of chances of wildfire smokes, control forest diseases and provision better habitat for wildlife. Specific results have been estimated for the program in each state. This includes reduction of the acres burned, number of high intensity wildfires and loss of houses due to wildfires. At this point, a question is presented in the booklet as to whether or not the respondent would support this program of prescribed fire with three options to answer: 1). Should, 2). Should not, 3). Do not know.

Page five of the booklet explains the cost of this program. A detailed explanation of possible funding sources is given along with results from this program. The willingness to pay elicitation question is presented here as follows:

If the Extended Prescribed Burning Program was undertaken it is expected to reduce the number of acres of wildfires shown in Figure 1 from the current average of approximately B acres each year to about C acres (See below table), for 25% reduction. The number of houses destroyed by wildfires is expected to be reduced from an average of D a year to about F each year.

Your Chance to Vote: *Your share of the Extended Prescribed Burning Program would cost your household $................a year. If the Extended Prescribed Burning Program were on the next ballot would you vote:*

1. *In favor*
2. *Against.*

Table 5-1 Current acres burning and reduced acres burning by prescribed burning program and number of houses to be saved

States	B(acre) (Current)	C(acre) (With program)	D(Current houses lost)	F(Houses lost with program)
California	362,600	272,500	30	12
Florida	200,000	150,000	43	25
Montana	140,000	105,000	20	8

Table 5-2 Burned acreage reduced and houses saved with prescribed burning program

States	Acreage (acre)	Number of houses saved
California	90,100	18
Florida	50,000	18
Montana	35,000	12

The sixth and seventh pages provide alternatives to prescribed fire mitigation program. This includes a mechanical fire fuel reduction program. For this program, description goes along with expected results. The mechanical fire fuel reduction program was described as follows:

Mechanical fire fuel reduction is very effective at lowering the height of vegetation that reduces the ability of fires to climb up to the top or crowns of the trees from the ground. This mechanical mowing would slow the growth of new vegetation with the layer of the mulch that acts as a barrier. Comparing to prescribed burning, this program is more expensive due to labor cost and equipment cost, food species for wildlife is reduced, but it will not produce any smoke, no damage to structures and no harm to fire professionals.

The willingness to pay question is asked to make sure that the respondent would to pay to support the program implementation and it is stated as follows:

If the Mechanical Fire reduction Program was undertaken instead of the Extended Prescribed Burning Program, it is expected to reduce the number of acres of wildfires shown in Figure 1 from the current average of approximately B acres each year to about C acres (See below table), for 25% reduction. The number of houses destroyed by wildfires is expected to be reduced from an average of D a year to about C (year).

Your Chance to Vote

Your share of this Mechanical Fire Fuel Reduction Program would cost your household $……………..a year. If the Mechanical Fire Reduction Program were on the next ballot would you vote:

1 In favor

2 Against.

The bid amounts denoted $X have been designed for both program and these amounts of mechanical fire fuel reduction are on average $10 higher that those of prescribed burning program (table 5-5).

Table 5-3 Current acres burning and reduced acres burning by mechanical fire fuel reduction program and number of houses to be saved

States	B(acre) (Current)	C(acre) (With program)	D(Current houses lost)	F(Houses lost with program)
California	362,000	272,500	30	12
Florida	200,000	150,000	43	25
Montana	140,000	105,000	20	8

Table 5-4 Burned acreage reduced and houses saved with mechanical fire fuel reduction program

States	Acreage (acre)	Number of houses saved
California	85,000	18
Florida	50,000	18
Montana	35,000	12

Table 5-5 Initial fuel reduction program random dollar bid amount design

Bid number	Prescribed burning	Mechanical fire fuel reduction
1	$10	$20
2	$20	$30
3	$30	$40
4	$40	$50
5	$60	$70
6	$90	$100
7	$120	$130
8	$150	$160
9	$250	$270
10	$350	$380

After the question on willingness to pay is asked, if a respondent indicated she or he would vote against the program, then they were asked an open- ended question: "Why did you vote this way?". The obtained reasons are analyzed for contents to classify answers by similar reasons given by the respondent. This open-ended response approach avoids having respondents fit themselves into pre-set protest categories or interviewers placing them into those categories (Loomis, Bair and Gonzales-Caban, 2002).

The final page of the booklet is the demographics section. The purposes why the respondents' demographics are recorded are given and along with other question on their location and experiences with fires in each state (Appendix 1).

2. SURVEY MODE

To get a representative sample in three states of California, Florida and Montana, a random digit dialing of the population has been used. The use of random dialing assures that nearly all households are eligible to be interviewed. This plays an important role in sample design making sure that households that do not put their phone number in phone book could be interviewed and making the sample more representative. In addition, with this random digit dialing approach, the sample would be balanced by males and females (Bair, 2001). Because of frequent forest fires, these people directly or indirectly are affected by wildfires. The surveys were conducted using phone-mail-phone approach. The initial phone interview lasted about 5 minutes with questions focusing on introduction of the survey purposes, having preliminary knowledge of respondents on fires, having address to send the in depth survey booklet. The individuals were asked to read the booklet prior estimated date phone interview. This is very difficult with commercial mailing lists as the majority of listed phone numbers are in the male's names. The phone interviews were conducted in English and Spanish in California and Florida, and only in English in Montana.

According to Loomis and Gonzales- Caban (1988), the phone-mail-phone approach provides very high quality comparing to a pure mail survey. This gives interviewees to see the hypothetical market with color pictures. Interviewing by phone would encourage respondents to answer all the questions yielding more complete surveys for each person. Meanwhile, in the pure phone survey respondents can not see and read anything leading to low rate of responses. However, phone-mail-phone is more expensive that mail survey but cheaper that in person interviews.

CHAPTER VI: RESULTS

In this chapter we present the results of the survey implementation and the hypothesis tests.

1. RESPONSE RATE ANALYSIS

1.1. Response rate of white people in California, Florida and Montana

Response rates (RR) are examined for white people in three states California, Florida and Montana and for Hispanics in Florida and Montana. There are two types of response rates to be examined: the first is screener response rate (or the first wave RR) and the second is in-depth interview response rate (or the second wave RR). The first wave RR is the percent of respondents from the total initial sample that has been contacted and those completed the initial interview. The percent of net sample completed in the in-depth interview is the second wave response rate. We can get the net sample by leaving out those respondents who refused to give their addresses, were not available, were not contacted by the end of the data period, moved to other places or the telephones were disconnected. Table 6-1 shows response rates of white people in CA, FL and MT. The response rates of these people in the first wave of interview in CA, FL and MT are 41.3%, 85.3% and 67.6% respectively. The chi-square statistic of the first wave response rate ($\chi^2 = 69.89$) is significant at the level of 1% and 5%. Therefore, we can infer that there is a statistically significant difference among response rates across white people in

CA, FL and MT to the initial phone call. If we compare this response rate of FL to that of MT, χ^2 is significant at the level of 5%, therefore RR of white people in FL is different from that of MT. With the first call for interviewing, white people in Florida have the highest response rate and the lowest response rate belongs to those people in California. This could be explained by the fact that people in Florida are mainly the retirees (35% of the completed interviews calculated from data of survey), meanwhile people in California are the busier with a more rushed life style (Retirees occupy 20.7% of the completed interviews).

In the second wave interview, the chi-square statistic is not significant at the level of 1% and 5%. The response percentages in three states CA, FL and MT in the second wave are similar (72.8% for CA, 72.2 for FL and 72.9 for MT).This means that response rates among white people in CA, FL and MT are not significantly different. Completing the more in-depth interview, we could see improvement in response rates of white people in CA and MT (31.5% and 5.3% respectively) compared to those rates of the first wave interview. This could be because of the reason that once the respondents received the booklet, they did realize the importance and benefits of the fire reduction programs or they could be impressed by the nicely designed booklet and the way the survey was carried out. In Florida, the tendency is opposite. The response rate is down by 13.3%. This may be because people recognized the length of time required to complete of the interview, then decided to quit the survey.

1.2. Response rate of Hispanic people in California and Florida

The survey of Hispanic people for two programs of fire fuel reduction has been carried out in California and Florida in Spanish. The Hispanics in FL have the RR of

84.7% in the first wave interview, and that indicator of the Hispanics in CA is 65.7%. The Chi-square statistic is significant at the level of 1% and 5% (table 6-2) in both wave interviews meaning that response rates of Hispanic people in FL and CA are statistically different or our null hypothesis on equality of response rates of Hispanic people in CA and FL is rejected. In the in-depth interview, the response rates of these people in two state CA and FL have decreased to 38.7% and 62.4%, respectively. The difference in response rates among Hispanic people in two states could be understood again by the fact that people in FL are mainly retirees and those people in CA mostly belong to the working class. Looking at responses rates of the first and second wave interview, we could see the second in-depth interview has lower percentages for both states CA and FL. The reduction of this indicator is 27% for the Hispanics in California and 22.3% for those people in FL. The high response rate of the Hispanics in FL in the first wave interview (84.7%) could be because the interview was done in Spanish and was appreciated much by respondents. However, once they received the booklet they realized the time commitment necessary to complete the second interview, therefore they did not complete the in-depth interview (Ellingson, 2003). This may be the reason why the response rates of the Hispanics in CA and FL states have dropped much from the first wave interview to the second wave one. Meanwhile, the white people in the same states have higher response rates in the in-depth interview in the survey. This means that these people accepted the time commitment for the in-depth interview in the initial interview or they may have recognized much necessity and benefit of fire fuel reduction programs.

Table 6-1 Response rates of white people in California, Florida and Montana

	California		**Florida**		**Montana**	
	Persons	%	Persons	%	Persons	%
1st wave						
Total initial sample contacted	794		626		602	
Completed initials	328	41.3	534	85.3	407	67.6
χ^2 of the 1st wave calculated	**69.89*****					
2nd wave						
Net sample for 2nd interviews	257		454		373	
Completed interviews	187	72.8	328	72.2	272	72.9
χ^2 of the 2nd wave calculated	**0.008**					
χ^2 critical at 0.05 and 0.01	**5.99 and 9.21**					
Degree of freedom	2					

Table 6-2 Response rates of Hispanic people in California and Florida

	California		**Florida**	
	Persons	%	Persons	%
1st wave				
Total initial sample contacted	1353		770	
Completed initials	889	65.7	652	84.7
χ^2 calculated of the 1st wave	**13.72*****			
2nd wave				
Net sample for 2nd interviews	795		553	
Completed interviews	308	38.7	345	62.4
χ^2 of the 2nd wave calculated	**24.48*****			
λ^2 critical at 0.05 and 0.01	**3.84 and 6.63**			
Degree of freedom	1			

2. REFUSAL TO PAY ANALYSIS

The recording of open-ended statements after respondents voted "no" to a specific fuel treatment program identified protest votes (Loomis, Bair and Gonzales-Caban, 2002). The reasons like opposition to government programs, stating the program would not work, opposed to taxes, etc are also considered to be protest votes. The reasons for the no votes by respondents like the program are just not worth or they cannot afford paying to programs are the non protest votes and show that the respondents are sticking to the contingent market. The refusals to pay in our study are examined for each category of people (the Whites and Hispanics) and for each program: prescribed burning and mechanical fire fuel reduction.

2.1. Refusals to pay of white people for prescribed burning program

From the survey data, responses are categorized and identified as protest and non protest (table 6-4) and summarized in table 6-3. Using Minitab, a statistical software package, the chi-square of protest versus non protest responses is computed. The calculated chi-square of 3.368 with degree of freedom of 2 indicates no statistically significant difference among white people in three states CA, FL and MT in the pattern of protest and non protest reasons for refusing to pay for prescribed burning program. We could say that the ratios between protest and non protest refusal to pay responses of white people among three states CA, FL and MT are equivalent to each other and independent of states. 6.2 % of respondents saying no to pay to RX program in MT is categorized as protest response and this is the highest percent among three states, 5.5 % of saying no to the bids for RX program in FL is the highest percent that is identified as non responses.

Table 6-3 Comparison of refusals to pay of white people for prescribed burning program

	California		**Florida**		**Montana**	
	Persons	%	Persons	%	Persons	%
Protest responses	8	4.3	14	4.3	17	6.2
Non protest responses	6	3.2	18	5.5	8	2.9
χ^2 **calculated**	**3.368**					
χ^2 **critical at 0.05 and 0.01**	**5.99 and 9.21**					
Degree of freedom	2					

Looking at reasons of protest and non protest responses in table 6-4, we could see that these reasons are very diverse from one state to another. They could be grouped approximately into the following categories:

Because interviewees themselves can not afford or it is unfair to expect them to pay

Interviewees' opinions to the program like program is not realistic, too expensive,

No benefit or no value from the programs for interviewees

Funding like using existing fund, no need more fund or these programs

Opposition to the taxes like taxes are too high already,...

Opposition to government program and distrust state and local agencies

These programs would cause wildlife problem like reduction of food...

These programs would cause environmental problems like smoke or too much burn of forest.

It is clear from table 6-4, white people in FL and MT gave more opinions on questions why they did not agree to pay to the bids the RX program. Ten persons from MT believed that RX program is not worth at all or too expensive, meanwhile more people in FL do not trust the state agencies or oppose to the tax. People in these two states also expressed the concern about wildlife and environment when program is implemented. People in CA could be with busier daily life; therefore they just provided only four types of reasons focusing on economic burden of the program implementation. However, there could be the fact that with severity of current fires, almost respondents in CA agreed to pay to the bid for RX program, only 5.9 % (11 persons) refused to pay, much lower percent comparing to other two states CA and MT. The percentages of agree to pay of white people in three states are similar to each other and all are over 90%.

Table 6-4 Reasons not to pay to the bids of white people for prescribed burning program

Opinions	California		Florida		Montana		N/ NP
	#	%	#	%	#	%	
Agreed to pay for the first and second bids	176	94	296	90.3	248	90.8	
Cannot afford	3	1.6	3	0.9	1	0.4	NP
Not worth it/too expensive	1	0.5	10	3			NP
Would not work/ not realistic/ use other ways			1	0.3	1	0.4	P
Use existing funds (or other source of funding)	4	2.1	3	0.9	4	1.5	P
Citizens should not have to pay/ unfair			1	0.3	2	0.7	P
Government should pay (Federal/State/county)			1	0.3	1	0.4	P
Opposed to government programs			1	0.3			P
Do not trust State, federal government					4	1.5	P
Opposed to taxes			4	1.2	3	1.1	P
Taxes already too high	2	1.1					NP
Urban-interface residents should pay (or affected people)			2	0.6	1	0.4	P
Logging is better and cheaper					1	0.4	NP
Better way to help forest					1	0.4	NP
Not the way to control fire safety					1	0.4	NP
Little risk for respondent/ no problem of mine			1	0.3			NP
Concern for wildlife			1	0.3			NP
Against program in general or not enough to make it worthwhile			1	0.3	1	0.4	NP
Need more information			1	0.3			NP
Smoke is a problem or it will burn too much			1	0.3	1	0.4	NP
Mixed feeling, all control burns have escaped control					1	0.4	NP
Other	1	0.5	1	0.3	1	0.4	P
Total protest (N)	**5**	**2.6**	**14**	**4.3**	**17**	**6.2**	P
Total non protest (NP)	**6**	**3.2**	**18**	**5.5**	**8**	**2.9**	NP

2.2. Refusal to pay to of white people for mechanical fire fuel reduction program

The same respondents were asked on the bids for mechanical fire fuel reduction program. Refusal to pay to the bids responses were also categorized and identified into protest and non protest responses for three states CA, FL and MT. Chi-square of 2.009 (table 6-5) has been calculated for protest and non protest responses of refusal to pay the bids. Comparing the calculated chi-square to the critical one at the level of 1% and 5%, it is obvious that there is no statistically significant difference among white people in three states in the pattern of saying no to the bids for mechanical fire fuel reduction program. However, looking at table 6-5 we could see that the mechanical fire fuel reduction program has been protested by quite many respondents in Florida and Montana. From 273 interviewees in MT, there were 85 households would not pay for the bids, and this number in FL was 59 households. Comparing this indicator of mechanical fire fuel reduction program to that of RX program, it could be deduced that people in three states CA, FL and MT would like to see RX implemented rather than mechanical fire fuel reduction program. Five persons in CA, 8 persons in FL and 5 persons in MT dislike mechanical fire fuel reduction program, RX program has been considered prior to mechanical fire fuel reduction by 5 persons in CA and 12 in FL. We did not see the similar opinions (table 6-4) in interviews with respondents on RX program.

The reasons of refusal to pay the bids for Mech program also could be grouped like that in RX program. However, respondents in MT expressed much concern about program itself and local people when the program is implemented such as necessity of the program, loss of jobs to local people or loss of timber (12 respondents), etc. Data from table 6-6 suggests that we should have more information on the program for people in

Florida and Montana such as timber thinning program (for logs), existing wild fire control programs, and existing fund for these activities.

Table 6-5 Comparison of refusals to pay of white people for mechanical fire fuel reduction program

	California		**Florida**		**Montana**	
	Persons	%	Persons	%	Persons	%
Protest responses	13	6.9	21	6.4	36	13.2
Non protest responses	12	6.3	38	11.6	49	17.9
χ^2 calculated	**2.009**					
χ^2 critical at 0.05 and 0.01	**5.99 and 9.21**					
Degree of freedom	2					

2.3. Refusal to pay of Hispanic people for RX program in California and Florida states

Our null hypothesis is that there is no difference in protest and non protest refusal to pay responses between Hispanic people in two states California and Florida for prescribed burning program. Comparing calculated chi-square to the critical ones (table 6-7), it is clear that the null hypothesis is not rejected meaning that the ratios of protest to non protest responses in CA and FL are equivalent to each other. However, in absolute number, in Florida 55 households did not agree to pay the bids, only 11 interviewees in California refused to pay.

Looking at reasons why these people did not want to pay (table 6-8), we could see that people in Florida expressed various opinions among which are 28 protest and 17 non protest responses. The reasons of protest focus mainly on opposition of government program, unfairness of expecting them to pay and using the existing fund for RX program. It could be thought that life style may contribute to making the difference in number of households saying no to the bids in California and Montana. This is one of matters that should be addressed in another contingent valuation study. This result also suggests that different information may be needed to convey the RX program such as available funds for this kind of activities in states, impact of the program on taxes or payment vehicle if the program is implemented so that respondents would not be reluctant to answer the questions.

Table 6-6 Reasons not to pay to the bids of white people for mechanical fire fuel reduction program

Opinions	California		Florida		Montana		N/
	#	%	#	%	#	%	NP
Agreed to pay for the 1st and 2nd bids	165	88.3	269	82	188	68.9	
Cannot afford	1	0.5	3	0.9			NP
No value/benefit or not necessary to intervene with wild land fires	1	0.5			1	0.4	NP
Not worth it/too expensive			13	3.9	3	1.1	NP
Not work/ not realistic/ use other ways			8	2.5	8	2.9	P
Use existing funds(No additional fund)	2	1.1	2	0.6	6	2.2	P
Citizens should not have to pay/ unfair or forest service has already money			1	0.3	1	0.4	P
Government should pay			1	0.3	1	0.4	P
Opposed to government programs or distrust State/fed government			1	0.3	5	1.8	P
Opposed to taxes (Tax already too high)			4	1.3	3	1.1	P
Urban-interface residents should pay	5	2.7	2	0.6			P
Little risk for respondent			1	0.3			NP
Concern for environment or mulch will become a fire problem			2	0.6	1	0.4	NP
Concern for wildlife (Reduce food..)	4	2.1	6	1.8	4	1.5	NP
Against program in general (method is unnatural, leave nature alone)	3	1.6	3	0.9	9	3.3	NP
Dislike the Mech program	3	1.6	8	2.5	5	1.8	NP
Preferred RX program	5	2.7			12	4.4	P
Not believable					4	1.5	P
Program will take away local jobs					1	0.4	NP
Program not necessary					1	0.4	P
Log it first					12	4.4	NP
Concerned about loggers					1	0.4	NP
Only at urban wild land interface					1	0.4	NP
Too many control burned already					1	0.4	NP
Not many fires in State					1	0.4	
Wants more information about program					2	0.7	NP
I don't know why and didn't want to say					2	0.8	P
Other/illegible			2	0.6			NP
Other	1	0.5	2	0.6			P
Total protest (N)	**13**	**5.3**	**21**	**6.4**	**36**	**13.2**	**P**
Total non protest (NP)	**12**	**6.3**	**38**	**11.6**	**49**	**17.9**	**NP**

Table 6-7 Comparison of refusals to pay of Hispanic people for prescribed burning program

	California		Florida	
	Persons	%	Persons	%
Protest responses	7	1.7	28	8.3
Non protest responses	4	1.3	17	5.1
χ^2 calculated	**0.008**			
χ^2 critical at 0.05 and 0.01	**6.635 and 3.841**			
Degree of freedom	1			

Table 6-8 Reasons not to pay to prescribed burning program bids of Hispanic people in California and Florida

Opinions	California		Florida		N/ NP
	Person	%	Person	%	
Agreed to pay for the first and second bids	301	97.7	300	87	
Cannot afford	1	0.3	6	1.7	NP
Not worth it/too expensive or no value	3	1	7	2	NP
Would not work/ not realistic/ use other ways	2		2	0.6	P
Other programs in booklet superior			2	0.6	NP
Use existing funds			8	2.3	P
Citizens should not have to pay/ unfair			7	2	P
Government should pay (Federal/State/county)	2		0	0	P
Opposed to government programs			7	2	P
Opposed to taxes			1	0.3	P
Urban-interface residents should pay			1	0.3	P
Little risk for respondent/ no problem of mine			1	0.3	NP
Concern for environment			0	0	NP
Concern for wildlife			0	0	NP
Against program in general			1	0.3	NP
Other/illegible			1	0.3	NP
Other	3	1	1	0.3	P
Total protest (N)	**7**	**1**	**28**	**8.3**	**P**
Total non protest (NP)	**4**	**1.3**	**17**	**5.1**	**NP**

2.4. Refusal to pay of Hispanic people for Mech program in California and Florida states

From the table 6-9, the protest rates for the mechanical fire fuel reduction program were 13.15 for Florida and 1.6% for California Hispanic people. The non protest response rates were 11.6% and 4.5%, respectively. The chi-square statistic is significant at the level of 5% meaning that there is statistically significant difference between Hispanic people in two states CA and FL in the scheme of protest and non protest reasons for refusing to pay the bids of Mech program. In general, we could see a substantial support of Hispanic people for Mech program as a means to reduce wildfires.

Table 6-9 Comparison of refusals to pay of Hispanic people for mechanical fire fuel reduction program

	California		**Florida**	
	Persons	%	Persons	%
Protest responses	5	1.6	44	13.1
Non protest responses	14	4.5	39	11.6
χ^2 **calculated**	**4.14***			
χ^2 **Critical at 1% and 5 %**	**6.635 and 3.841**			
Degree of freedom	1			

Looking at table 6-10 of reasons not to pay the bid amount for the Mech program, Hispanic people in two states have nearly the same opinions. These people do not like Mech program rather than the RX one. They also paid attention to environment, wildlife if the program is implemented. As other options, the Hispanic people in FL expressed more concerns about the program implementation than people in CA. This could be the fact that at the time of survey, the wild fires in FL were more severe than those in CA. Thus people in FL looked at the survey with high expectation and more serious consideration. Hispanic people in California have lower percentage of protest and non protest responses than people in Florida for mechanical fire fuel reduction program. Again, people in Florida may not want to see more human intervention to the nature.

Table 6-10 Reasons not to pay to mechanical fire fuel reduction program bids of Hispanic people

Opinions	California		Florida		N/ NP
	Person	%	Person	%	
Agreed to pay for the first and second bids	289	93.9	262	76	
Cannot afford			6	1.7	NP
Not worth it/too expensive, or no value	3	1	16	4.6	NP
Would not work/ not realistic/ use other ways			9	2.6	P
Use existing funds	2	1.1	1	0.3	P
Citizens should not have to pay/ unfair			11	3.2	P
Government should pay (Federal/State/county)			6	1.7	P
Opposed to government programs			0	0	P
Opposed to taxes			7	2	P
Urban-interface residents should pay or others	5	2.7	5	1.4	P
Little risk for respondent/ no problem of mine			5	1.4	NP
Concern for environment			2	0.6	NP
Concern for wildlife	4	2.1	6	1.7	NP
Against program in general or method is unnatural/leave nature alone			1	0.3	NP
Dislike Mech program	3	1.6			
Preferred RX program	5	2.7	3	0.9	P
Other/illegible			0	0	NP
Other	1	0.5	5	1.4	P
Total protest (N)	**5**	**1.6**	**44**	**12.7**	**NP**
Total non protest (NP)	**14**	**4.5**	**39**	**11.3**	**P**

3. REGRESSION OUTPUT DISCUSSION

3.1. Discussion of regression output of logit models for white people

3.1.1. Prescribed burning program logit model

Development of logistic regression began with building the initial model based on the selected variables (table 6-11). To reflect the impact of geographic difference on probability of voting for the proposed fuels reduction programs, we include in the model 2 dummy variables: California and Florida. Montana State is subsumed as the base case. Besides these, we also include interaction terms of state variables and bid amount. The purpose of this is to see the impact of bid amount in each state on probability of voting. The logistic regressions were run with Eviews software.

Table 6-11 includes regression results from 2 options of including and excluding income variable, and two cases in each option of including and excluding protest responses for prescribed burning program (For detail of regressions, see appendix 2). California state variable is significant at the 0.05 and 0.01 level for all 4 models. Meanwhile, the Florida state variable is significant at 0.05 and 0.1 level in 4 regressions. None of state bid interaction terms is significant at any level. In term of our hypothesis regarding states, table 6-11 indicates that the state logit intercepts do shift up the logit functions by the values of coefficients but do not rotate these functions in comparison to the Montana case. The null hypothesis of Ho: $\beta_2 = 0$ and $\beta_4 = 0$ is rejected, and Ho: $\beta_3 = 0$ and $\beta_5 = 0$ is failed to be rejected. In all 4 logit regressions, the bid variable is negative and statistically significant suggesting that the higher the dollar amount the respondent was asked to pay the less likely they would pay.

Comparing 2 options with and without income variable, we see that the variables that are statistically significant in the option without income are also statistically significant with income variable included. The income variable itself is statistically insignificant. According to Greene (2000), this missing data case is avoidable. As suggested by Storandt, in this case we could drop out the income variable.

To see how the performance of the logistic models is, we can use the McFadden R-squared. In linear model, the R^2 is used to reflect the fitness of sample to population, McFadden R^2 has the same function of R^2 in logistic models (John Whitehead, 2003). McFadden R^2 of option without income variable is quite better than that of the option with income and this indicator of the case with protest responses included is worse than that with protest responses excluded.

3.1.2. Mechanical fire fuel reduction program logit model

For this program, four regressions have been run with two options of with and without income. In each option, there are two models with protest responses included and excluded. The results of regressions (For detail of regressions, see appendix 2) from table 6-12 show that only bid variable is statistically significant. The negative sign of bid variable is as expected and indicates that the higher bid amount is asked, fewer people would pay. In term of our hypothesis test, the state variable is not significant at the 10% level in any of the regressions. The state bid interaction term is also statistically insignificant at the 10% level in all of the regressions. The geographic difference in general does not have an independent effect on support for the mechanical fuel reduction program.

The income variable turns out to be statistically significant at the level of 5%. This means that we should include income in our regression for mechanical fuel reduction program. From McFadden R^2, it is also suggested that the sample with income included would better fit to the population.

4. DISCUSSION OF LOGIT MODEL REGRESSION OUTPUT FOR HISPANIC PEOPLE

For Hispanic people in two states California and Florida, tables 6-13 and 6-14 present the regression results for prescribed burning and mechanical fuel reduction programs, respectively (For detail of regressions, see appendix 2). State variable and state bid interaction terms in all regressions are statistically insignificant. The null hypothesis of zero coefficients of state variable and state bid interaction terms is failed to be rejected indicating that none of these intercepts could shift or rotate the logit function index. This suggests that Hispanic people would support for two fuels reduction program not depending where they are.

The bid variable is negative and statistically significant at 1% and 5% level for prescribed burning and mechanical fuel reduction programs, respectively. This follows the economic theory and the higher the dollar amount of bid asked, the less likely they are to vote in favor of the program. From the level of statistical significance, it could be induced that there is a higher support among Hispanic people in two states for the prescribed burning program.

Besides the bid variable, the education variable is statistically significant at 5% and 1% levels for 2 programs. The negative sign of the education variable suggests that the more education a respondent holds, the less likely they are to vote in favor of two fuels reduction programs. For the prescribed burning program, this may be because of the fact the local people did not want to see any human intervention with natural forests. For the mechanical fuel reduction program, this may be because of the intrusive nature of the program. A higher level of education could possibly lead to a less supportive attitude of programs that do not closely mimic a natural process.

When the income variable included, the nature of regression results is unchanged and this variable is statistically insignificant. Therefore, we can drop it out or we can use the regression outcomes with it included. As in the prescribed burning program, this is an avoidable case of missing data.

Table 6-11 Logit model with pooled data of three state white people: California, Florida and Montana for prescribed burning program

Variables	Without Income Variable		With Income Variable	
	Protests included	Protests excluded	Protests included	Protests excluded
	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)
Constant	1.3316	2.5524	1.6792	2.6962
	(1.82)*	**(3.14)*****	**(2.16)****	**(3.15)*****
Age	-0.0056	-0.0063	-0.0039	-0.0033
	(-0.95)	(-0.99)	(-0.62)	(-0.47)
CA State	0.9188	1.2129	0.9442	1.2347
	(2.39)**	**(2.75)*****	**(2.32)****	**(2.67)*****
CA Sate-RXBid	-0.0011	-0.0019	-0.0015	-0.0024
	(-0.69)	(-1.08)	(-0.86)	(-1.32)
Educ	-0.025	-0.1074	-0.0518	-0.1336
	(-0.57)	**(-2.21)****	(-1.0862)	**(-2.5111)****
ExpSmoke	0.0967	0.2589	0.0249	0.2636
	(0.35)	(0.88)	(0.08)	(0.83)
FL State	0.799	0.7492	0.6421	0.6458
	(2.47)**	**(2.18)****	**(1.94)***	**(1.79)***
FL State-RXBid	-0.0026	-0.0025	-0.0015	-0.0012
	(-1.61)	(-1.43)	(-0.86)	(0.65)
OwnHome	0.1041	0.23345	0.0468	0.1578
	(0.43)	(0.91)	(0.17)	(0.55)
RerspProb	0.31112	0.3938	0.2651	0.3598
	(1.38)	(1.59)	(1.12)	(1.38)
RXBid	-0.0035	-0.004	-0.0036	-0.0039
	(-3.69)***	**(-3.95)*****	**(-3.61)*****	**(-3.76)*****
WitnessFire	0.0204	0.0601	-0.0259	0.0103
	(0.092)	(0.25)	(-0.11)	(0.04)
Income			2.74E-06	3.72E-06
			(0.89)	(1.12)
Mean dependent var	0.6848	0.7229	0.6895	0.7283
Log-likelihood	-369.1614	-322.5994	-333.3721	-290.3293
Restr.log likelihood	-401.3484	-359.9883	-361.1514	-322.909
LR statistic (11 df)	64.3739	74.7777	55.5587	65.16
Probability (LR stat)	**1.41E-09*****	**1.50E-11*****	**1.44E-07*****	**2.55E-09*****
McFaddenR-squared	0.080197	0.103681	0.076919	0.10089

* Significance at 10% ** significance at 5% *** significance at 1%

Table 6-12 Mechanical fire fuel reduction program logit model with pooled data of three state white people: CA, FL and MT

Variables	Without Income Variable		With Income Variable	
	Protests included	Protests excluded	Protests included	Protest excluded
	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)
Constant	-0.0225	0.1355	0.2467	0.46
	(-0.035)	(0.21)	(0.37)	(0.65)
Age	-0.0006	-0.0018	0.004	0.0032
	(-0.11)	(-0.35)	(0.74)	(0.57)
CA State	0.1601	0.1813	0.1116	0.1337
	(0.51)	(0.54)	(0.34)	(0.38)
CA Sate-MechBid	-0.002	0.0016	0.0018	0.0013
	(1.32)	(1.018)	(1.12)	(0.82)
Educ	0.0245	0.0274	-0.0144	-0.0173
	(0.65)	(0.68)	(-0.35)	(-0.39)
ExpSmoke	-0.2689	-0.2182	-0.3763	-0.3249
	(-1.13)	(-0.89)	(-1.47)	(-1.24)
FL State	0.4287	0.3063	0.31	0.1946
	(1.59)	(1.07)	(1.1)	(0.64)
FL State-MechBid	-0.0018	-0.0016	-0.0008	-0.0004
	(-1.12)	(-0.96)	(-0.44)	(-0.21)
OwnHome	-0.1394	-0.0952	-0.2423	-0.1923
	(-0.69)	(-0.46)	(-1.08)	(-0.83)
RerspProb	0.1203	0.1	0.1092	0.0856
	(0.63)	(0.53)	(0.55)	(0.41)
MechBid	-0.0033	-0.0036	-0.0033	-0.0037
	(-3.27)***	**(-3.45)*****	**(-3.17)*****	**(-3.42)*****
WitnessFire	-0.1549	-0.0839	-0.1574	-0.0818
	(-0.82)	(-0.43)	(-0.79)	(-0.39)
Income			5.62E-06	6.06E-06
			(2.21)**	**(2.22)****
Mean dependent var	0.6848	0.4548	0.4219	0.468
Log-likelihood	-369.1614	-443.411	-436.786	-398.1
Restr.log likelihood	-401.3484	-465.1143	-458.2636	-418.855
LR statistic (11 df)	64.3739	43.4057	42.958	41.50865.16
Probability (LR stat)	**1.41E-09****	**9.23E-06****	**2.30E-07****	**4.03E-05****
McFaddenR-squared	0.045063	0.046661	0.04687	0.049549

* Significance at 10% ** significance at 5% *** significance at 1%

Table 6-13 Prescribed burning program logit model with pooled data of two state Hispanic people: California and Florida

Variables	Without Income Variable		With Income Variable	
	Protests included	Protests excluded	Protests included	Protests excluded
	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)
Constant	3.2464	3.45	2.7736	3.1963
	(3.68)***	**(3.59)*****	**(2.98)*****	**(3.19)*****
Age	-0.0078	-0.0055	-0.0073	-0.0051
	(-1.11)	(-0.71)	(-0.95)	(-0.62)
CA State	0.38	0.3562	0.6165	0.55
	(1.1)	(0.94)	(1.71)	(1.41)
CA Sate-RXBid	0.0021	0.0019	0.002	0.0019
	(1.28)	(1.1)	(1.19)	(1.06)
Educ	-0.114	-0.1225	-0.0872	-0.1332
	(-2.1)**	**(-2.07)****	(-1.48)	**(-2.08)****
ExpSmoke	0.878	0.3579	0.2792	0.2555
	(1.53)	(1.3)	(1.05)	(0.91)
OwnHome	-0.3838	-0.2461	-0.2329	-0.3
	(-1.59)	(-0.96)	(-0.9)	(-1.09)
RerspProb	-0.0324	0.0556	-0.0889	0.0546
	(-0.11)	(0.18)	(-0.31)	(0.17)
RXBid	-0.0039	-0.0042	-0.0039	-0.0043
	(-3.24)***	**(-3.29)*****	**(-3.01)*****	**(-3.18)*****
WitnessFire	0.007	0.0895	0.1681	0.1999
	(0.027)	(0.31)	(0.61)	(0.68)
Income			-4.6E-06	6.77E-06
			(-0.985)	(1.16)
Mean dependent var	0.749	0.792	0.7426	0.775
Log-likelihood	-279.63	-241.198	-250.6124	-224.066
Restr.log likelihood	-300.835	-258.15	-272.5734	-244.1272
LR statistic (11 df)	42.412	33.9	43.922	40.1223
Probability (LR stat)	**2.76E-09****	**9.28E-05****	**3.46E-06****	**1.61E-05****
McFaddenR-squared	0.07	0.065	0.08	0.082

* Significance at 10% ** significance at 5% *** significance at 1%

Table 6-14 Mechanical fire fuel reduction program logit model with pooled data of two state Hispanic people: California and Florida

Variables	Without Income Variable		With Income Variable	
	Protests included	Protests excluded	Protests included	Protests excluded
	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)
Constant	3.028	3.3438	2.6931	2.9032
	(3.97)***	**(4.18)*****	**(3.34)*****	**(3.5*****
Age	0.0005	0.0033	-0.0005	0.0033
	(0.09)	(0.49)	(-0.08)	(0.47)
CA State	0.1953	-0.1644	0.3417	0.1077
	(0.68)	(-0.54)	(1.13)	(0.34)
CA Sate-MechBid	0.0018	0.0024	0.0017	0.0022
	(1.3)	(1.64)	(1.15)	(1.46)
Educ	-0.2033	-0.1969	-0.1782	-0.1818
	(-4.32)***	**(-4.05)*****	**(-3.49)*****	**(-3.5)*****
ExpSmoke	0.2151	0.1039	0.0943	-0.0138
	(1.02)	(0.47)	(0.43)	(-0.06)
OwnHome	-0.0287	-0.1	-0.0928	-0.1806
	(-0.14)	(-0.48)	(-0.43)	(-0.8)
RerspProb	-0.1319	-0.0986	-0.23	-0.1832
	(-0.56)	(-0.39)	(-0.93)	(-0.71)
MechBid	-0.002	-0.0029	-0.0022	-0.0029
	(-1.92)**	**(-2.48)****	**(-1.9)****	**(-2.45)****
WitnessFire	0.0377	0.126	0.1357	0.2153
	(0.17)	(0.55)	(0.59)	(0.88)
Income			9.87E-07	3.13E-06
			(0.25)	(.69)
Mean dependent var	0.589	0.64	0.581	0.616
Log-likelihood	-368.1918	-330.61	-328.9267	-305.698
Restr.log likelihood	-390.7	-346.873	-350.7962	-324.3325
LR statistic (11 df)	45.023	32.519	43.7389	37.269
Probability (LR stat)	9.14E-07	0.000162	3.67E-06	5.08E-05
McFaddenR-squared	0.057	0.046	0.062	0.057

* Significance at 10% ** significance at 5% *** significance at 1%

5. EQUALITY OF VARIABLE COEFFICIENTS ACROSS STATES FOR DIFFERENT GROUPS OF PEOPLE AND PROGRAMS

To test whether the coefficients in logit models 1 and 2 vary with state variable or not, we perform the likelihood ratio test. To do this, we set up logit models like models 1 and 2 without including the state variables for 2 programs for each category of people and each state. The log likelihood from these models is called unrestricted ($LL_{unrestricted}$) (See appendix 3). To calculate the R-squared, we run pooled data models for each category of people for each program to get restricted log likelihood (See appendix 4 and 5).

Calculated χ^2 = $-2(LL_{restricted}-LL_{unrestricted})$ (Gujarati, 2003)

We have two options: including and excluding protest responses and in each option there are 2 cases: with and without income. The degree of freedom is the number of restrictions in each model. The results of Calculated χ^2 are illustrated in tables 6-15, 6-16, 6-17, 6-18, 6-19, 6-20.

From tables 6-15, 6-16, 6-17, 6-18, 6-19, 6-20 below, it is clear that all χ^2 calculated are greater than the critical χ^2 at 1% level. There is significant difference among coefficients. Therefore the null hypothesis on equality among coefficients of logit models without state variable is rejected. For each option of including and excluding protest responses and each case of with and without incomes, the coefficients of bid amounts and other variables for white and Hispanic people in each fire fuel reduction program are different from each other and these coefficients vary with state variable. It can be stated that where people live has an effect on how the resident responded to the survey with 99% levels of confidence, if a resident lives in California, and then she or he would vote in favor or against a fire fuel reduction program differently than people living in Florida or Montana.

Option 1*. Protest responses are included*

Table 6-15 Likelihood ratio test of coefficient equality across States for white people for prescribed burning (RX) (Protest responses are included)

Models	Log likelihood		All 3 models		CA vs FL		CA vs MT		FL vs MT	
	W/o Inc*	W/t Inc*	W/o Inc*	W/t Inc*	W/o Inc*	W/t Inc*	W/o Inc*	W/t Inc*	W/o Inc*	W/t Inc*
CA White	-84.5	-76.9								
FL White	-144.5	-120.7								
MT White	-136.4	-131.8								
Sum of unrestricted	-365.4	-329.4	-365.4	-329.4	-229.0	-197.6	-220.9	-208.7	-280.9	-252.5
Pooled (Restricted)	-401.3	-361.2	-401.3	-361.2	-250.4	-214.4	-241.3	-230.1	-307.8	-274.3
Calculated χ^2			**71.84**	**63.52**	**42.7**	**33.5**	**40.92**	**42.84**	**53.88**	**43.56**
Critical χ^2 1%			**31.99**	**34.8**	**20.09**	**21.66**	**20.09**	**21.66**	**20.09**	**21.66**
DF			16	**18**	8	**9**	8	**9**	8	**9**

(W/o Inc* is without income and W/t Inc* is with income)

Table 6-16 Likelihood ratio test of coefficient equality across States for white people for mechanical fire fuel reduction (Mech) (Protest responses are included)

Models	Log likelihood		All 3 models		CA vs FL		CA vs MT		FL vs MT	
	W/o Inc*	W/t Inc*	W/o Inc*	W/t Inc*	W/o Inc*	W/t Inc*	W/o Inc*	W/t Inc*	W/o Inc*	W/t Inc*
CA White	-117.2	-109.6								
FL White	-195.9	-164.6								
MT White	-159.3	-154.								
Sum of unrestricted	-472.4	-428.2	-472.4	-428.2	-313.1	-274.2	-276.5	-263.7	-355.2	-318.6
Pooled (Restricted)	-503.7	-458.3	-503.7	-458.3	-332.9	-291.8	-293.4	-283.1	-378.6	-338.5
Calculated χ^2			**62.72**	**60.08**	**39.46**	**35.22**	**33.9**	**38.8**	**46.82**	**39.94**
Critical χ^2 1%			**31.99**	**34.8**	**20.09**	**21.66**	**20.09**	**21.66**	**20.09**	**21.66**
DF			16	18	8	9	8	9	8	9

Table 6-17 Likelihood ratio test of coefficient equality across States for Hispanic people for prescribed burning and Mechanical fire fuel reduction programs (Protest responses are included)

Models	RX program				Mech Program			
	W/o income		W/t income		W/o income		W/t income	
	Log likeli-Hood	Two models	Log likeli-Hood	Two models	Log likeli-Hood	Two models	Log likelihood	Two models
CA Hispanics	-115.6		-108.31		-172.52		-164.52	
FL Hispanics	-161.67		-139.44		-191.97		-159.86	
Sum of unrestricted	-277.27	-277.27	-247.75	-247.75	-364.49	-364.49	-324.38	-324.38
Pooled (Restricted)	-300.83	-300.83	-272.57	-272.57	-390.7	-390.7	-350.79	-350.79
Calculated χ^2		**47.12**		**49.64**		**52.42**		**52.82**
Critical χ^2 1%		**20.09**		**21.66**		**20.09**		**21.66**
DF		8		9		8		9

***Option 2**. Protest responses are excluded*

Table 6-18 Likelihood ratio test of coefficient equality across States for white people for prescribed burning (Protest responses are excluded)

Models	Log likelihood		All 3 models		CA vs FL		CA vs MT		FL vs MT	
	W/o Inc*	W/t Inc*	W/o Inc*	W/t Inc*	W/o Inc*	W/t Inc*	W/o Inc*	W/t Inc*	W/o Inc*	W/t Inc*
CA White	-71.27	-65.85								
FL White	-125.78	-101.29								
MT White	-119.46	-116.44								
Sum of unrestricted	-316.5	-283.6	-316.5	-283.6	-197.1	-167.1	-190.7	-182.3	-245.2	-217.7
Pooled (Restricted)	-401.3	-361.2	-401.3	-361.2	-250.4	-214.4	-241.4	-230.1	-307.8	-274.3
Calculated χ^2			**169.66**	**155.14**	**106.66**	**94.46**	**101.28**	**95.6**	**125.2**	**113.08**
Critical χ^2 1%			**31.99**	**34.8**	**20.09**	**21.66**	**20.09**	**21.66**	**20.09**	**21.66**
DF			16	18	8	9	8	9	8	9

Table 6-19 Likelihood ratio test of coefficient equality across States for white people for mechanical fire fuel reduction program (Protest responses are excluded)

Models	Log likelihood		All 3 models		CA vs FL		CA vs MT		FL vs MT	
	W/o Inc*	W/t Inc*	W/o Inc*	W/t Inc*	W/o Inc*	W/t Inc*	W/o Inc*	W/t Inc*	W/o Inc*	W/t Inc*
CA White	-107.6	-99.9								
FL White	-183	-151.5								
MT White	-143.6	-138.								
Sum of unrestricted	-434.3	-389.4	-434.3	-389.4	-290.6	-251.4	-251.3	-237.9	-326.6	-289.5
Pooled (Restricted)	-503.8	-458.3	-503.8	-458.3	-332.9	-291.8	-293.4	-283.1	-378.6	-338.5
Calculated χ^2			**138.98**	**137.66**	**84.5**	**80.82**	**84.34**	**90.2**	**103.86**	**98.1**
Critical χ^2 1%			**31.99**	**34.8**	**20.09**	**21.66**	**20.09**	**21.66**	**20.09**	**21.66**
DF			16	18	8	9	8	9	8	9

Table 6-20 Likelihood ratio test of coefficient equality across States for Hispanic people for prescribed and mechanical fire fuel reduction programs (Protest responses are excluded)

Models	RX program				Mech Program			
	W/o income		W/t income		W/o income		W/t income	
	Log likeli-hood	Two models	Log likeli-hood	Two models	Log likeli-hood	Two models	Log likeli-hood	Two models
CA Hispanics	-103.54		-98.11		-166.99		-158.81	
FL Hispanics	-135.66		-120.1		-160.35		-142.64	
Sum of unrestricted	-239.2	-239.2	-218.21	-218.21	-327.34	-327.34	-301.45	-301.45
Pooled (Restricted)	-300.83	-300.83	-272.57	-272.57	-390.7	-390.7	-350.79	-350.79
Calculated χ^2		**123.26**		**108.72**		**126.72**		**98.68**
Critical χ^2 1%		**20.09**		**21.66**		**20.09**		**21.66**
DF		8		9		8		9

6. MEAN AND MEDIAN WILLINGNESS TO PAY DISCUSSION

The first step in calculation of mean and median WTP is to run the original logit models (1 and 2) with only significant independent variables (table 6-21, 6-22, 6-23, 6-24). These models will exclude variables that may be highly correlated with each other (See appendix 6 and 11). For example, education has a significant impact on the probability of a yes vote for a bid amount, it may be somewhat related to income or where the respondent lives.

Table 6-21 Results of regression with significant independent variables for white people in three states (Protest responses included)

Described burning program			Mechanical fire fuel reduction program		
White people in California					
Variable	Coefficient	t-Statistic	Variable	Coefficient	t-Statistic
c	1.813490	6.010637			
RXBid	-0.004611	-3.507788			
White people in Florida					
c	1.632138	7.627468	c	0.237248	0.706202
RXBid	-0.005938	-4.558692	MECHBid	-0.003944	-2.814101
			Income	8.42E-06	2.025419
			Witnessfire	-0.689370	-2.569453
White people in Montana					
c	0.956570	4.505331	C	-0.169898	-0.876829
RXBid	-0.003502	-3.703512	MECHBid	-0.003329	-3.303312

Table 6-22 Results of regression with significant independent variables for the Hispanics (Protest responses included)

Described burning program			Mechanical fire fuel reduction program		
Hispanic people in California					
Variable	Coefficient	t-Statistic	Variable	Coefficient	t-Statistic
c	3.225258	3.458445			
RXBid	-0.001619	-1.514047			
Educ	-0.125873	-1.766844			
Hispanic people in Florida					
c	1.150849	5.854723	C	3.339505	3.023298
RXBid	-0.003467	-2.968625	MECHBid	-0.001976	-1.858630
			Educ	-0.217423	-2.882761

Table 6-23 Results of regression with significant independent variables for white people in three states (Protest responses excluded)

Described burning program			Mechanical fire fuel reduction program		
White people in California					
Variable	Coefficient	t-Statistic	Variable	Coefficient	t-Statistic
c	2.258908	6.466939	c	-0.050411	-0.071263
RXBid	-0.005656	-3.989075	MECHBid	-0.002556	-2.077504
			Age	0.015921	1.448731
			Expsmoke	-0.581146	-1.586407
			Income	3.48E-06	0.960401
White people in Florida					
c	4.353172	3.398218	C	2.958628	2.480765
RXBid	-0.006965	-4.773026	MECHBid	-0.003989	-2.758247
Educ	-0.210963	-2.568442	Educ	-0.174620	-2.175025
Ownhome	0.726814	1.947560	Income	7.96E-06	1.791021
Respprob	0.848499	2.090014	Witnessfire	-0.578897	-2.072756
White people in Montana					
c	1.283829	5.474667	C	-0.220056	-0.723343
RXBid	-0.004034	-4.056234	MECHBid	-0.003701	-3.432797
			Income	8.38E-06	1.629510

Table 6-24 Results of regression with significant independent variables for the Hispanics (Protest responses excluded)

Described burning program			Mechanical fire fuel reduction program		
Hispanic people in California					
Variable	Coefficient	t-Statistic	Variable	Coefficient	t-Statistic
c	4.044987	4.047998			
RXBid	-0.002326	-2.080471			
Educ	-0.151679	-2.014295			
Hispanic people in Florida					
c	0.503512	1.451708	c	3.615561	3.026155
RXBid	-0.003895	-2.946244	MECHBid	-0.002842	-2.493458
Income	2.26E-05	2.507560	Eeduc	-0.202880	-2.492769

The mean and median WTPs are calculated for two options: including protest and excluding responses for each of two fuel reduction programs. The following formulae

(Hanneman, 1989) are used for calculating the mean and median WTP of 2 options: including and excluding protest responses

Mean WTP= (ln (1+exp(α)))/B. Where α is the product of the coefficient and mean values of all independent variables excluding the bid coefficient. B is the absolute value of the bid coefficient.

Median WTP= α/B

By using the above formulae, WTP_{CA}^{White}, WTP_{FL}^{White}, WTP_{MT}^{White}, $WTP_{CA}^{Hispanic}$, $WTP_{FL}^{Hispanic}$ for each program and each option have been calculated and illustrated in table 6-25 and 6-26.

4.1. ***Option 1:*** *Protest responses are included.*

The confidence intervals of 95% and 90% were calculated using a simulation technique developed by Park *et al.,* (1991) that uses the means of constant independent variables from computed regression outcomes and the variance-covariance matrix. Looking at 90% confidence intervals (table 6-25) for white and Hispanic people for prescribed burning and mechanical fuel reduction programs, it is obvious that these confidence intervals overlap each another. This tells us there is no statistical difference between the mean WTPs for these groups of people. The mean WTPs of white people for three states in RX program are quite similar to each other and the gap between WTPs of white people for Mech program in Florida and Montana is closer. Hispanics in California are willing to pay at least three times as much as for RX program compared to the same group of people in Florida. One possibility for the higher willingness to pay of Hispanics in California for RX program is that the prescribed burning program seems to be highly necessary for local people, or it may be labor intensive and could provide a substantial number of jobs for Hispanics in California. However, the large confidence intervals suggest these differences are not statistically significant. The bid coefficients of white and Hispanic people in California were insignificant for mechanical fuel reduction program, thus precluding calculation of statistically significant estimates of WTP.

Table 6-25 Mean and median annual WTP for RX and MECH programs and confidence intervals at 95%, 90% (Protest responses included)

White people				
	Mean($)	Median($)	Confidence Intervals around Means	
RX program			95%	90%
White CA RX	427.794	394.845	314.75 - 811.74	327.94 - 694.42
White FL RX	304.917	274.84	238.17 - 468.74	245.23 - 429.87
White MT RX	360.925	269.296	269.24 - 655.68	280.5 - 568.42
Mech program				
White CA Mech				
White FL Mech	207.333	59.668	140.74 - 535.01	146.25 - 409.19
White MT Mech	183.78	-51.033	131.17 - 377.23	137.78 - 317.33
Hispanic people				
RX program				
Hispanic CA RX	1269.96	1185.39	622.32 - 17822	674.23 - 9870.1
Hispanic FL RX	411.26	331.98	283.93 - 1035	297.06 - 795.44
Mech program				
Hispanic CA Mech				
Hispanic FL Mech	414.74	120.73	232.97 - 3589.2	249.47 - 2024.7

*4.2. **Option 2**: Protest responses are excluded.*

With protest responses excluded, we also use the same approach to calculate mean WTP as in the first option. The results are presented in table 6-26. An overlapping confidence 90% is an indication that there is no statistical difference among WTPs for white and Hispanic people in three states for two programs of fire fuel reduction. This is the same conclusion as in the case with including the protest responses. The gaps between mean WTPs of the same groups of people among these states are similar to that in the first option. These gaps are quite large, but with wide confidence intervals leading to insignificant difference between WTPs of the same groups of people among three states for two proposed programs. The large confidence intervals could be partly due to small sample size. Therefore, the null hypothesis on similarity among mean WTPs of white and Hispanic people in three states for RX and Mech programs cannot be rejected at the 90% confidence level. With protest responses excluded, the white people in California expressed the support to mechanical fire fuel reduction program with mean WTP of $402.97.

Table 6-26 Mean and median WTP for RX and Mech programs and confidence intervals of 95%, and 90% (Protest responses excluded)

White people				
	Mean ($)	**Median ($)**	**Confidence Intervals around Means**	
RX program			95%	90%
White CA RX	416.95	399.38	322.52 - 661.93	334.88 - 598.94
White FL RX	305.04	230.25	246.09 - 470.58	256.34 - 436.24
White MT RX	382.08	320.95	285.37 - 623.68	297.39 - 553.05
Mech program				
White CA Mech	402.97	299.26	242 - 2436.3	260.56 - 1308.3
White FL Mech	229.74	101.71	151.03 - 728.98	159.45 - 515.49
White MT Mech	207.94	39.74	150.94 - 385.56	157.12 - 338.77
Hispanic people				
RX program				
Hispanic CA RX	991.84	946.75	573.85 - 6186.9	613.04 - 3472.7
Hispanic FL RX	393.36	330.86	267.12 - 956.32	279.48 - 760.58
Mech program				
Hispanic CA Mech				
Hispanic FL Mech	397.5	260.18	258.93 - 1652.7	273.9 - 1032.9

From values in tables 6-25 and 6-26, mean WTP of Hispanic people in California for prescribed burning program is three times greater than that of white people. This could be that case that Hispanic people may expect job creation by the program. On the other hand, using the logit coefficients for the whites and Hispanics in California (tables 2-21, 2-22, 2-23, 2-24) with demographic characteristics cuts the difference in WTP in nearly half, suggesting that demographic play a large role in the WTP difference. From table 6-27, the number of Hispanic people in California having problems with wildfires is greater than white people. Especially, among the Hispanics, seven respondents have had their home burned, so did 21 neighbors of them. These reasons could be the ones leading to the WTP difference between the whites and Hispanics in CA. For the white and Hispanic groups of people in Florida, the mean WTP for two proposed programs are quite similar to each other.

Table 6-27 Opinions of white and Hispanic people in California and Florida on consequences of wild fires

	Bother you	Visual bother	Physical bother	Both types of bother	Psychological bother	Respiratory problem	Serious respiratory Prob.	Modest respiration Prob.	Burn home	Burn neighbor home	Evacuate home
California											
White people	80	14	19	44	2	36	3	16	0	14	10
Hispanic People	93	21	42	26	3	40	7	19	7	21	10
Florida											
White people	173	69		100		75	22	20	8	23	48
Hispanic People	171	59		113		65	20	24	8	14	20

7. SCOPE TEST

7.1. Pooled data model for three states

We pool data of three states for the scope test model for prescribed burning and mechanical fire fuel reduction programs. Here we try to test whether acreage reduction of burned forests affects on probability of saying yes to the proposed bid amount. The scope test is implemented for white and Hispanic people and with the assumption that benefits of prescribed burning and mechanical fire fuel reduction programs are transferable among these three states of California, Florida and Montana.

White people

Table 6-28 Logit regression results of scope test for white people

Variables	RX program		Mech Program	
	Coefficient	t-statistic	Coefficient	t-statistic
Constant	1.4638	(1.84)	0.021	(0.03)
Acrereduction	1.17E-05	**(2.4)*****	6.37E-06	**(1.55)***
RXBid	-0.00449	**(-6.36)*****		
MechBid			-0.003	**(-4.49)*****
Age	-0.00323	(-0.51)	0.0039	(0.73)
Educ	-0.0472	(-0.99)	-0.0117	(-0.29)
ExpSmoke	0.0247	(0.08)	-0.3698	(-1.45)
Income	2.81E-06	(0.91)	5.40E-06	(2.13)
OwnHome	0.0228	(0.09)	-0.2139	(-0.96)
RerspProb	0.268	(1.14)	0.1095	(0.55)
WitnessFire	-0.07	(0.06)	-0.192	(-0.98)

* Significance at 10% ** significance at 5% *** significance at 1% (For details of regressions, see appendix 12)

With degree of freedom of 777 (n-number of independent variables= 787-10=777) and t-critical at 10%, 5% and 1% levels are 1.282, 1.645, 2.326 respectively, acrereduction variable is statistically significant at 0.1 and 0.01 level. The sign of this variable is positive telling us that white people in three states CA, FL and MT would be willing to pay more if more acreage of burned forests is proposed in RX and Mech programs. The null hypothesis is rejected and our conclusion is that WTP is sensitive to reduction of burned forest acreage.

Hispanic people

Table 6-29 Logit regression results of scope test for Hispanic people

Variables	RX program		Mech Program	
	Coefficient	t-statistic	Coefficient	t-statistic
Constant	1.493	(1.32)	1.7872	(1.83)
Acrereduction	2.27e-05	**(3.4)***	1.47E-05	**(2.63)***
RXBid	-0.002716	**(-3.26)***		
MechBid			-0.001152	**(-1.65)**
Age	-0.0069	(-0.89)	-0.000218	(-0.03)
Educ	-0.088	(-1.49)	-0.1766	(-3.47)
ExpSmoke	0.2527	(0.96)	0.08188	(0.37)
Income	-4.28E-06	(-0.92)	1.11E-06	(0.28)
OwnHome	-0.2388	(-0.93)	-0.0989	(-0.46)
RerspProb	-0.095	(-0.33)	-0.2344	(-0.94)
WitnessFire	0.166	(0.61)	0.1355	(0.59)

* Significance at 10% ** significance at 5% *** significance at 1% (For details of regressions, see appendix 12)

Looking at the sign of the acrereduction variable and its t-statistic, we could see the same tendency as for white people for both RX and Mech program. The positive sign tells us that the more acreage of reduction of burned forest acreage is proposed, the more likely the Hispanics say yes to the bid amounts. The acrereduction variable is statistically significant at 0.01 level, therefore we accept the alternative with $\beta_1 > 0$ at this level. The high values of t-statistic demonstrate that the Hispanics took the amount of acreage reduction seriously. The scope test shows us that scope or change in burned forest reduction is statistically significant for the WTP or WTP is sensitive to amount of acreage reduction.

7.2. Reduced models

To determine WTP function for acreage reduction, we eliminated insignificant variables: Age. Educ, Expsmoke, Income, Ownhome, Respprob and Witnessfire in order to focus the impact of significant variables on probability of voting to bid amounts. After that we run the reduced logit models for RX and Mech programs and white and Hispanic people on acreage reduction and bid amounts.

Table 6-30 Reduced logit regression output for White people

Variables	RX program		Mech Program	
	Coefficient	t-statistic	Coefficient	t-statistic
Constant	0.7899	**(3.04)***	-0.4819	**(-2.16)**
Acrereduction	1.17E-05	**(2.7)***	1.05E-05	**(2.9)***
RXBid	-0.004538	**(-6.91)***		
MechBid			-0.00311	**(-4.96)***

(For details, see appendix 12)

Median WTP function for prescribed burning program:

Median WTP ($/a household/a year)= 174.06+ 0.00258 Acrereduction

Median WTP function for mechanical fire fuel reduction program:

Median WTP($/a household/a year) = -154.95+ 0.00338 Acrereduction

Table 6-31 Reduced logit regression output for Hispanic people

Variables	RX program		Mech Program	
	Coefficient	t-statistic	Coefficient	t-statistic
Constant	-0.2229	(-0.6249)	-0.9574	(-3.09)***
Acrereduction	2.50E-05	**(4.69)***	2.03E-05	**(4.69)***
RXBid	-0.00247	**(-3.19)***		
MechBid			-0.000649	(-1.02)

(For details, see appendix 12)

Median WTP function for prescribed burning program:

Median WTP($/a household/a year) = -90.24+ 0.0101 Acrereduction

Median WTP function for mechanical fire fuel reduction program:

Median WTP ($/a household/a year) = -1475.19+ 0.0313 Acrereduction

(Coefficients of these functions are obtained by dividing coefficients by absolute values of bid coefficients from regression)

From policy aspect, these WTP functions are very useful for policy makers and managers. They can find out WTP with a certain number of acreage of forests that no longer burn by plugging that acreage number into these functions. Table 6-32 provides estimated values per household for preventing fires on between 10,000 and 100,000 acres of forests in CA, FL and MT states with using the formula mean WTP= $(\ln(1+\exp(\alpha)))/B$. Where α is the product of the coefficient and mean values of all independent variables excluding the bid coefficient, B is the absolute value of the bid coefficient (These data from tables 6-29 and 6-30).

Table 6-32 Willingness to pay to reduce acres of forests in California, Florida and Montana

Acreage reduction	White People		Hispanic people	
	Mean WTP for RX Program($)	Mean WTP for Mech Program($)	Mean WTP for RX Program($)	Mean WTP for Mech Program($)
10000	274.58	167.96	286.15	593.93
15000	283.84	174.94	312.58	645.71
20000	293.25	182.12	340.59	701.05
25000	302.81	189.53	370.15	760.07
30000	312.51	197.16	401.23	822.87
35000	322.35	205.01	433.78	889.52
40000	332.32	213.08	467.75	960.07
45000	342.42	221.37	503.09	1034.57
50000	352.65	229.88	539.73	1113.03
55000	363.00	238.61	577.61	1195.46
60000	373.46	247.57	616.62	1281.83
65000	384.05	256.74	656.72	1372.10
70000	394.74	266.14	697.83	1466.21
75000	405.53	275.75	739.85	1564.09
80000	416.42	285.57	782.73	1665.62
85000	427.41	295.62	826.40	1770.72
90000	438.49	305.87	870.78	1879.25
95000	449.67	316.34	915.81	1991.08
100000	460.93	327.01	961.44	2106.08

From mean WTP per household, we can calculate the population WTP in three states of CA, FL and MT and whole USA for each program and each group of people by multiplying mean WTP per household computed in this study by the number of households in each state and whole country. The number of households of CA, FL and MT in 2003 is 12,040,000; 6,741,000 and 365,000 respectively and total number households of USA in 2003 is 108, 980,000 (http//jan.mannlib.cornell.edu/data-sets/specialty/FLO/F15.xls, accessed on November, 13, 2004). Then the benefits of each state and whole country for each program can be calculated for each level of acreage reduction.

8. CONCLUSION AND POLICY IMPLICATION

President George W. Bush proposed the forest initiative in 2002 stating that the American people, their property and our environment, particularly the forests and rangelands of the West, are threatened by catastrophic fires and environmental degradation. One of reasons of wildfires is significant fire fuel accumulation. With fire fuel accumulated, forests become unhealthy and vulnerable to unnaturally severe wildfires. Preventing these wild fires is very urgent for all agencies, organizations and whole society. The Forest Initiative proposed some ways to reduce fire fuel to curb the severity of future wildfires. Among these ways are two means of preventing wildfire: prescribed burning and mechanical fuel reduction techniques. Prescribed burning is a fire purposely set in a designed area to accomplish one or more specific objectives such as removal of underbrush or dead wood to reduce available fire fuel and increase the ability to control future wildfires. Mechanical fire fuel reduction technique mechanically removes smaller trees and vegetation in order to prevent wildfires from reaching the tops of mature trees. This study focused on examination of people's support to two extended fire fuel reduction programs: prescribed burning and mechanical fire fuel reduction in three states of California, Florida and Montana. This support could be determined through response rate, protest rate to the survey and willingness to pay on these programs.

For collecting data for determining the benefits of these programs, dichotomous choice referendum contingent valuation technique has been used. To analyze the results, the binary logit models have been estimated for each proposed program. These models have been constructed for white people in three states of California, Florida and Montana, and for Hispanic people in two states of California and Florida. The response rate analysis consisted of the initial interview and in-depth interview responses. For white people in CA, FL and MT, the chi-square statistic of the first wave response rate ($\chi^2 =$ 69.89) is significant different at the level of 1% and 5%. Therefore, we can infer that there is a statistically significant difference among response rates across white people in CA, FL and MT to the initial phone call. In the second wave interview, the chi-square statistic is not significant at the level of 1% and 5% meaning that response rates among white people in CA, FL and MT are not significantly different. For Hispanic people in two states of California and Florida, the survey for two programs of fire fuel reduction has been carried out in Spanish. The Chi-square statistic is significant at the level of 1% and 5% in both wave interviews. Thus we could conclude that response rates of Hispanic people in FL and CA are statistically different.

If the respondent was not willing to pay for two prescribed burning and mechanical fire fuel reduction programs, even $1, then they were asked why. These "no" responses were divided into protest and non-protest responses. Minitab has been used for calculating the chi-square of protest versus non protest responses for white and Hispanic people and for each of proposed programs. For white people in prescribed burning program, there was no statistically significant difference among these people in three states CA, FL and MT in the pattern of protest and non protest reasons for refusing to pay for this program. In mechanical fire fuel reduction, there is also no statistically significant difference among white people in three states in the pattern of saying no to the proposed bids. By the same token, we tested for the ratios of protest to non protest responses for Hispanic people in CA and FL for Hispanic and for prescribed burning program and we found the equivalence of these ratios. For mechanical fire fuel reduction program, Hispanic people in California have a different scheme of protest and non protest reasons for refusing to pay the bids of this program compared to the same group of people in Florida. For each group of people and each proposed program, reasons not to pay the bids also have been discussed.

The next hypothesis we evaluated was whether the state of residence had an influence on voting for two proposed program of fire fuel reduction. We examined this by developing a logit models with state variables and bid- state interaction variables and t- test has been used for this examination. The logit models have been estimated with pooled data from three states of CA, FL and MT for white and Hispanic people and for prescribed burning and mechanical fire fuel reduction programs. There are two options with and without income variable and in each option there are two cases of including and excluding protest responses. In total, sixteen logit models have been constructed. For White people with prescribed burning, the state logit intercepts do shift up the logit functions by the values of coefficients but do not rotate these functions in comparison to the Montana case. This says that the geographic difference has an impact on probability of voting for this proposed program. None of bid- state interaction terms is significant meaning that the bid amount does have any impact on probability of voting in each state. For the mechanical fire fuel reduction program, state variables and bid- state interaction variables are not significant at 10% level showing us that geographic difference does have an independent effect on support for this program. Another 8 logit models have been estimated for Hispanic people in California and Florida in two fire fuel reduction programs. State variable and state bid interaction terms in all regressions are not statistically insignificant. This suggests that Hispanic people would support for two fuels reduction program not depending where they are.

To see if the coefficients of logit models vary with state variables or not, we performed the likelihood ratio test. The chi-squares for each group of people and each proposed program have been calculated for two options with and without including protest responses and using restricted and unrestricted log likelihoods. All calculated chi squares are greater than critical ones at level of 1% saying that there is significant difference among coefficients and these coefficients vary with state variables. It can be stated that where people live has an effect on how the resident responded to the survey with 99% levels of confidence.

Mean willingness to pay has been computed for the two fuel reduction options including and excluding protest responses. The confidence intervals were calculated using a simulation technique developed by Park *et al.,* (1991). The found confidence intervals overlap each other for white people in three states of CA, FL and MT and Hispanic people in two states of CA and FL for two fire fuel reduction programs suggesting no significant difference in WTP.

The question raised here is how we can use these findings for policy application or is the WTP transferable among three states or not?. Table 6-32 summarizes all of the tests of transferability. A Yes means test suggests it is transferable.

Table 6-33 Transferability of mean willingness to pay

Index	**Transferability**			
	Income included		**Income excluded**	
	Protest response included	Protest response excluded	Protest response included	Protest response excluded
Prescribed burning for white people in CA, FL and MT				
1. Intercept shifter (State logit intercepts do shift up logit functions)	NO	NO	NO	NO
2. Bid-state interaction terms (don't rotate the logit functions)	YES	YES	YES	YES
3. Likelihood ratio test (Coefficients vary with state variable)	NO	NO	NO	NO
3. WTP test	YES	YES	YES	YES
Mechanical fuel reduction for white people in CA, FL and MT				
1. Intercept shifter (State logit intercepts are insignificant)	YES	YES	YES	YES
2. Bid-state interaction terms are insignificant)	YES	YES	YES	YES
3. Likelihood ratio test (Coefficients vary with state variable)	NO	NO	NO	NO
3. WTP test	YES	YES	YES	YES
Prescribed burning for Hispanic people in CA, FL				
1. Intercept shifter (State logit intercepts are insignificant)	YES	YES	YES	YES
2. Bid-state interaction terms (are insignificant)	YES	YES	YES	YES
3. Likelihood ratio test (Coefficients vary with state variable)	NO	NO	NO	NO
3. WTP test	YES	YES	YES	YES
Mechanical fuel reduction for Hispanic people in CA, FL				
1. Intercept shifter (State logit intercepts are insignificant)	YES	YES	YES	YES
2. Bid-state interaction terms (are insignificant)	YES	YES	YES	YES
3. Likelihood ratio test (Coefficients vary with state variable)	NO	NO	NO	NO
3. WTP test	NA	NA	NA	NA

Looking at table 6-32, for white people with prescribed burning program, two criteria of intercept shifter and likelihood ratio test say that survey responses are not transferable among three states of CA, FL and MT. However, the bid-state interaction terms and mean WTP test show the transferability of WTP at least for three states of CA, FL and MT in our study. From economic point of view, the insignificance of bid-state interaction terms and mean WTP among these four criteria would be more important than the other two ones in examining the transferability of WTP among three states; therefore we could believe that mean WTP is transferable among three states in our study. For white people with mechanical fire fuel reduction program, and Hispanic people with prescribed burning program, three criteria of intercept shifter, bid-interaction terms and WTP test indicate transferability of WTP among three states of CA, FL and MT. We also believe that WTP is transferable among states for these groups of people and proposed programs. Because bid was not statistically significant, we couldn't perform the WTP test for Hispanic people in two states of CA and FL in mechanical fire fuel reduction program, therefore WTP test criterion of this group of people is not applicable (NA). However, it seems that WTP perhaps would be transferable among states with statistical significance of bid variable and large confidence interval.

With the assumption of transferability of WTP, we performed the scope test. With using pooled data from three states of CA, FL and ML for white people and two states of CA and Fl for the Hispanics, the logit models have been estimated for each group of people and each proposed program. The acrereduction variable is statistically significant at 0.01 level for all logit models. This shows us that scope or change in burned forest reduction is statistically significant for the WTP or WTP is sensitive to amount of acreage reduction.

California, Florida and Montana are located in the West coast, East coast and Northern Rocky mountains, respectively of the United State of America (US). Among these states there exist many different features including racial composition, languages, income levels, geographic differences and of course the level of wild fires. However, we found that willingness to pay to two fire fuel reduction programs is transferable among these states. Is WTP transferable among other states of USA?. This matter is left for future study.

CHAPTER VII: PRE-TEST OF CONTINGENT VALUATION METHOD IN VIETNAMESE CONTEXT: THE CASE OF FOREST FIRE PREVENTION

I. APPLICATION OF CONTINGENT VALUATION METHOD IN DEVELOPING COUNTRIES

In developing countries, contingent valuation (CV) has become an important tool for estimating willingness to pay (WTP) to public good and environmental resources (Memon and Matsuka, 2002). The use of contingent valuation method focuses on measuring the value of environmental and health related outcomes from projects, policies and regulations (Whittington, 2002). The CVM survey have been administered to obtain residents' WTP for improved water supply in different localities of the world like Tunisia by Alexander A. McPhai (1994) on connection of households' water to piped water system, Burkina Faso by Altaf and Hughes (1994) on toilet, connection to the sewage system, region-wide waste water treatment, in Vietnam by Dang Minh Phuong and Chennat Gopalakrishnan on loss of water resources due to pesticide contamination in Mekong delta and in the Philippines by Donald T. Laura *et, al.*(1993) for determining the household demand for improved sanitation services and other countries. Applications of CVM have involved both rural and urban populations. From Food and Agriculture Organization (FAO) summaries of selected papers on application of CVM in developing countries, we could see that this method has been used quite widely in these countries. More and more international donor agencies and development proponents are increasingly putting CV techniques to use in project and policy appraisal as part of their everyday operations work (Whittington, 1996). In Vietnam, in May 2004 the Economy and Environmental Economics Program in South East Asia has funded a training course on CVM application introduced by Professor Dale Whittington from University of North Carolina at Chapel Hill and Professor Wictor Adamowicx of the University of Alberta.

Contingent valuation method was originated in developed countries and has been using frequently in these nations. For application of CVM in less developed countries, it is advised to take the characteristics of developing countries into account.

Characteristics of developing countries (From www.google.com, assessed on July 2nd):

- Income on a real per capita basis is 50 to 100 times larger in rich countries as in poor countries.
- Income growth is relatively rapid, but much of it is used by population growth, limiting growth of per capita income
- Population growth is higher in low income countries that in high income countries, although they slowed in countries in the last decades. Underdeveloped countries have younger populations with higher natural rates of population growth.
- Urbanization is less in developing countries than in developed countries. The share of population that is urbanized correlates strongly with the level of economic development.
- The gap between the rich and the poor is larger with economic development.

- High rate of illiteracy in rural and mountainous areas.
- Massive shift from agriculture to industry and services.
- Land reform is the most widely publicized form of income redistribution in developing countries, but it requires strong government power.
- Developing nations are debtor nations that borrow capital from more developed nations. These nations may borrow technology and ideas at a lower initial cost and risk.

1.1. Determining survey mode

According to FAO (2002), various survey methods are possible. However, the in-person interviews would be the most appropriate one for developing countries. This could be explained by the followings:

+ In-person interviews require a large amount of labor, but labor in developing countries is quite cheap and the local people can be used for these interviews; data collected is high quality one

+ The telephone surveys are less expensive but in many areas of developing countries, we cannot find telephone services. If there is telephone service, then it is expensive and telephone book does not exist, so we would have a biased sample reflecting high income. In the case we can use telephone for surveys, and then we can't have a long description of the scenario or use photographs or visual aids.

+ The mail surveys are even less expensive than telephone surveys. However, we would have a very low rate of responses that do not satisfy the purpose of our study. As mentioned in the characteristics of developing countries, people in rural and mountainous areas have a low rate of literacy leading to low initiative to take part surveys. As from my experience in doing participatory rural appraisal (PRA) for rural infrastructure projects funded by World Bank in Danang province of Vietnam, people in remote areas do not want to participate in surveys because they are too busy with working in field and they are shy and do not know much about surveys in general. Therefore, they rarely respond to the mail survey. On the other side, the mail surveys also make it difficult to ask questions that depend on the answer to previous questions, as is the case with follow-up questions about WTP.

With the above reasons, in-person interviews would be more practical and cheaper in the context of developing countries.

1.2. Survey implementation

Whittington (2002) believes that inconsistent results that one often finds in CV results are due to poorly trained enumerators and the resulting enumerator bias. Researchers from developed countries coming to do CVM in a developing country often have a short time stay and do not know well the practical issues involved in sampling. Therefore, training enumerators is an important task for researchers in developing countries. Interviewers should be clearly aware of the concept of maximum willingness to pay and other economic value concepts and have a correct translation into local language. As I know from PRA survey, the training of trainer's course often is held and pilot study is implemented before any regular survey.

1.3. Contingent valuation scenario

From experience of Whittington (2002), well crafted contingent valuation scenario would provide good data for our study. Crafting a good CV scenario turns out to be far harder that is commonly recognized. It is the single largest hurdle to the achievement of a high quality CV study. Whittington suggested that focus groups should be used and pretest carried out as well. Local people in developing countries have a lot of difficulties in understanding the hypothetical nature of the survey, therefore the CV researcher must be able to put herself or himself in the place of a respondent and understand how a respondent would consider the different facets of the hypothetical nature that she or he is being asked to evaluate (Whittington, 2002). A good CV scenario should be designed to be realistic and for respondents to take the hypothetical choice seriously (Whittington, 1996). According to Whittington (1996), the more seriously a respondent considers the choice, the less hypothetical the scenario is likely to seem. In the study on household demand for improved sanitation services in Calamba, the Philippines, Laura *et al., used* local enumerators that have experiences in doing household survey. These enumerators also received training in 4 different areas: The technology of improved sanitation, the mechanics of questionnaire completion, the contingent valuation method for eliciting willingness to pay responses and quality control. These researchers also used 3 week period for pre-testing and focus group.

1.4. Ethical issue in CVM survey

People in developing countries in general and in Vietnam in particular, receive much funding from international donors for different purposes such as poverty reduction, infrastructure development, education activities, etc. Therefore, when outsiders (maybe CV researchers) talk about some projects, these people believe that those projects are real even they are told that these projects are hypothetical.

At present, dichotomous CVM is used widely and has many advantages. The implementation of this type of CVM requires that several split samples of respondents receive different randomly assigned prices or bid amounts for the good or service described in the CV scenario. Because of the perception mentioned above, local people may confuse or misunderstand why there are different prices or bids mechanism required by CV technique. This might create a great public concern where the survey is implemented. In 1994, Professor Dale Whittington used referendum CVM in study for World Bank. The study was designed to estimate households' demand for improved water services in a small town in Mozambique. He randomly assigned five different prices to sub-samples of respondents. At the briefing the finding to local authorities, there was a controversy that why different households were asked to pay different prices. This did not seem fair to people in the town. This may have led to public uncertainty and confusion about the costs of improved water services in the town (Whittington, 1996).

As clear that people in developing countries live close to each other. That's why information spreads very fast among them. If we do a CV survey in a small area that respondents can talk to each other on prices or bid asked to pay, then this does not secure accuracy of our finding. As CV researchers, we should be aware of this situation. This happened to the study in Semarang, Indonesia by Professor Dale Whittington in 1995. What happened is that in one community the neighborhood leader tried to spread word throughout the community to answer no to their valuation question (Whittington, 1996). Again, the hypothetical choice may be understood in a wrong way.

1.5. Should respondents be compensated?

Theoretically, we could enclose 1 or 2 dollar bill with our survey booklet to respondents in mail survey. Xu and *et al.*, used a 2 RMB (Chinese currency and 1$=8.3 RMB) as a token of appreciation. This is understood that this 1 or 2 dollar bill is just a symbol expressing the appreciation of researchers to respondents. This is not certainly payment to respondents in the survey in developed countries. People in developing countries are accustomed to subsidy and they often ask for payment from interviewers. This happened to Professor Whittington when he was doing CV survey in Guatemala City (Whittington, 1996). Whittington thought that paying to respondents is somewhat self-serving. This obviously cut in researcher's limited budgets, but that in itself does not mean it would not be a good thing to do. He believes that he never actually has seen any evidence of the effects that paying respondents in developing countries had on survey administration. In participatory rural appraisal I participated, we paid to respondents in the surveys. The payment was equivalent to wage of one working day at local price for one day participating in the survey.

2. PRE-TEST OF CONTINGENT VALUATION METHOD IN VIETNAMESE CONTEXT: THE CASE OF FOREST FIRE PREVENTION

2.1. Objective of the pilot study

The objective of the study is to see how the CVM would work in Vietnam context using a small sample of respondents for forest fire prevention program. The performance of CVM could be evaluated through identifying response rate, protest rate, determining WTP of households to the program implementation and general reaction of people to CVM .We also want to test out the questionnaires designed to identify and correct potential problems.

2.2. Elicitation format of WTP value

Up to now in CVM, the following WTP value elicitation formats have been used:

- The open-ended direct elicitation format
- The bidding game elicitation format

- Payment card elicitation format
- Single bounded dichotomous elicitation format
- Multiple bounded dichotomous single bounded.

In our study, the payment card elicitation method is used. The payment card method was developed by Mitchell and Carson as an alternative to the bidding game (Mitchell and Carson, 1989). This method would increase the response rate, meanwhile allowing to maintain the properties of the direct question approach. The payment card does this by displaying a range of dollar amount including zero on a card, and allowing the respondent to circle their maximum WTP. In some ways, the payment card resembles a familiar pledge card used by charities or conservation organizations to elicit donations.

The payment card method has some advantages. It is good for a small sample study. In developing countries (including Vietnam), people are not routinely asked their opinions on policies, fearful of government and local authorities (Xu *et al.*, 2004-drafted). Therefore the tendency of yes saying may be exacerbated in public surveys. This could be avoided by using the payment card method. Further, a respondent liking the program but with a low WTP, can circle a low monetary amount that may reflect their true WTP rather then feeling compelled to answer yes to a monetary amount higher than they are able to pay. The payment card also helps us avoid misunderstanding ethical issues that could happen in dichotomous CVM as mentioned in the section 1-4.

2.3. Estimation of willingness to pay

In payment card, respondents are presented an ordered list of bids from which respondents choose their maximum amount they are willing to pay. Suppose that X_{iL} is the maximum dollar threshold that the *i*th individual would agree to pay for and X_{iU} be the minimum dollar the *i*th individual would agree to pay for maximum WTP_i lies somewhere in the switching interval [X_{iL}, X_{iU}] (Welsh and Poe, 1998). With this way, the WTP responses are elicited in form of intervals instead of point valuations and individual WTP values are estimated by using parametric models (Xu *et al.*, 2004, drafted). Another way is the conservative lower bound approach. With this approach, WTP is estimated by simply using the monetary amount revealed by the respondent as an indicator of their maximum WTP. To evaluate how WTP varies with demographics of the respondent, we can use ordinary least square (OLS) regression, or a tobit model to estimate a WTP, if many zero responses are obtained. A probit model will used to find out how the probability of being willingness to pay anything changes with different levels of the independent variables.

Ordinary least square (OLS), also known as the method of least squares, is a technique used to determine how one quantity Y (the dependent variable) changes a another quantity X (the independent variable) is varied, when it is assumed that a linear dependency would describe this relationship. Usually one is in possession of data consisting of pairs of observations (x; y), and the task is to determine the (assumed) linear relationship that holds between X and Y. OLS provides such a linear relationship. The main use of determining this linear relationship is to predict the value of Y on some other X which is not in the data set. We can use software Eviews to find this linear relationship with the available data set.

We can use tobit regression to estimate WTP for fire prevention program. This tobit model originally was developed by James Tobin (Gujarati 2003). Statistically, the tobit model can be expressed as follows:

$Y_i = \beta_0 + \beta_1 X_i + u_i$

According to Grogan-Kaylor and Otis, when most of values of a dependent variable are zero, the use of OLS regression is likely to lead to biased results. Tobit regression is a technique that appropriate for dealing with a continuous variable in which a large number of the values are zero. The coefficients in OLS and tobit models can be interpreted like any other regression coefficients (Gujarati, 2003). Software "Eviews" enables us to estimate tobit model in our study.

According to Gujarati (2003), the normal cumulative distribution function (CDF) is useful in many cases where one simply wants to explain the presence or absence of some phenomenon like WTP. The estimating model emerging from the normal CDF is popularly known as the probit model. As logit model, the probit model is applied to the cases where the dependent variable is either nominal or ordinal, and has two or more levels, and the independent variables are any mix of qualitative and quantitative predictors. In our case study we use to explain why some households would not pay anything and why some households would pay. Like logit or logistic regression, the users of probit focus on a transformation of the probability that Y, the dependent, equals. Where the logit transformation is the natural log of the odds ratio, the function used in probit is the inverse of the standard normal cumulative distribution function.

The probit model:

$Y = \beta_0 + \beta_1 X_i + u_i$

The CDF of probit is:

$$F(X) = \int_{-\infty}^{X_0} \frac{1}{\sqrt{2\sigma^2 \pi}} e^{-(X-\mu)^2/2\sigma^2}$$

Where X_0 is some specific value of X.

Regression coefficients of probit models are interpreted as effects on a cumulative normal function of the probabilities that Y=1. From estimated regressions, we can calculate the Z scores and by using standard normal distribution table, Z scores are translated into probabilities.

In practical term, probit models come to the same conclusions as logistic regression and have the drawback that probit coefficients are more difficult to interpret. The logit and probit regression models regress a function of the probability that a case falls in a certain category of Y, on a linear combination of X variables. The "right hand side" of the logit and probit, then, are the same as they are in the classical linear regression model. The slope coefficients tell us the effect of a unit change in X on a function of the probability of Y. We can use software "Eviews" to estimate probit models with available data set.

2.4. Survey design

2.4.1. Collecting background data for survey design

Providing respondents with an informative, accurate, and descriptive survey instrument elicits as close as possible representation of the value they place on fire break establishment and maintenance program. To accomplish this goal, we used four methods to retrieve information on forest fires of HoaBinh province in last year and the first 6 months of 2004. HoaBinh province has been chosen because it has quite large area of forest burned in 2003. It is a mountainous province with the forestry area of ¾ of total natural area. In one of its district, local people have built fire breaks for their forests and these fire breaks have developed their function of forest protection. The first method is World-Wide Web belonging to Department of Forest Ranger of Vietnam Ministry of

Agriculture and Rural Development. This web site posts information on last year forest fire statistics, reasons of wild fires, solutions to be applied to control and reduce forest fires and other information that is necessary for fire management. This page also provides information on fire breaks, guidance on their establishment and success of their use in HoaBinh and other province in Vietnam. The second important source of information, not only for obtaining data, but also in revising of the survey was annual report on forest fires of HoaBinh province forest ranger department and discussion with staff of the department. The report provided information on characteristics of forests in the province, forest fires of last year, reasons of these fires and measures applied on controlling these fires, solutions to prevent forest fires for 2004 including using fire breaks and other instruments. This report provided a clear picture of forest fires in HoaBinh last year. Discussion was held with vice director of HoaBinh province Forest Ranger Department and staff of Natural Resources Division of Forest Ranger Department. During meeting with these people, information concerning forest fires in HoaBinh, and further contacts were established, example of fire breaks establishment by local people in next district has been discussed. This experience was very helpful in revising the questionnaire. The third information source is HoaBinh statistics of 2002. This provided us information relating to many fields of whole province and each district of the province. This information is used in designing survey and through the survey process. The last method used in collecting data is in-person interview.

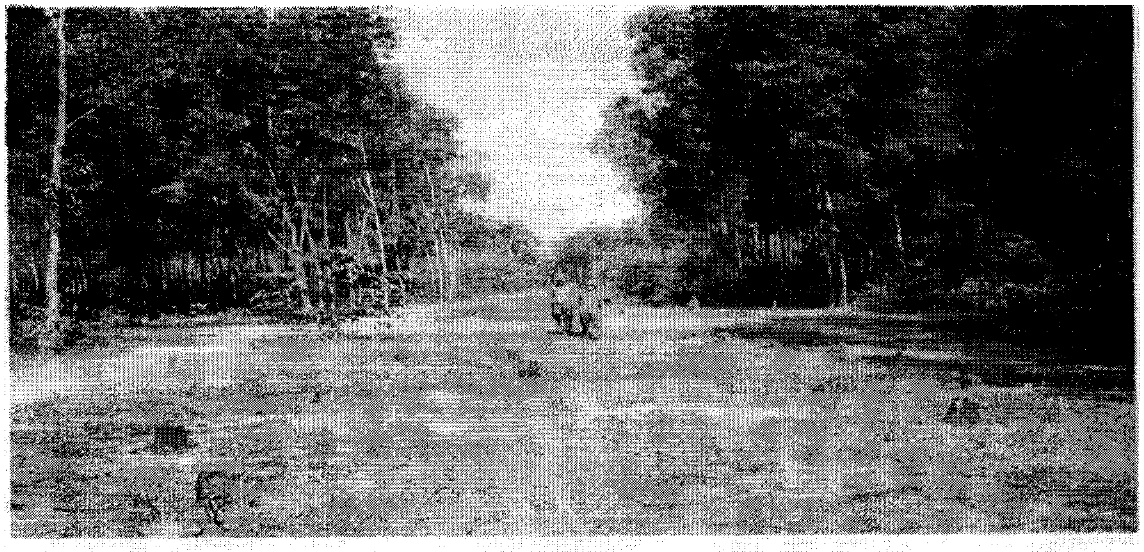
2.4.2. Survey features

The detailed description of the resource to be valued is required for obtaining accurate benefit estimates using CVM. The opening of the survey is introduction of the purpose of the survey and emphasizing that there would be no wrong or right answers and completion of the survey does not require any training and special skills. The respondents' answers would be used as only inputs for the research at Vietnam Forestry University and information from respondents is kept confidential (Appendix 1).

Forest fires in Vietnam Figure 3

In the next section, forest fire problem is presented and consequences of these fires have been estimated for whole province for 2003. From this situation, the discussion on possible solutions for forest fires has been presented. Among these solutions is establishment of fire breaks. An example of fire break establishment by local people in the next district is introduced to respondents in the survey.

The proposed program is extended fire break establishment and maintaining on 30,000 hectares of forests (about 30 % of natural area) in whole province for each coming year. Total 75 km of fire breaks are planned to be constructed in the proposed program for next year. The estimation of the area for fire break establishment and maintaining is in line with the policies from Department of Forest Rangers of the province.



• Duờng băng cản lửa rộng 20 m

Fire breaks with width of 20 meters Figure 4

Of course the benefits of the proposed program such as: protection of existing forests, reduction of flooding in rainy season and increase water supply in dry season, quicker access to control fires in large tracts of forested land, greater protection to residential areas in wooded areas, increased wildlife habitat diversity with open space in wooded area, being used as access roads for timber harvesting operations also are described.

Before WTP elicitation question, respondents are asked questions on role of fire breaks in forest protection and reduction of natural hazards and opinions on whether fire breaks should or should not be used in the province. This aims on providing respondents with more information of forest fires and forest fire breaks. The question who pay for the cost of the proposed program implementation is read to respondents. The payees are those who benefit from forests such as forest enterprises, forest loggers, forest ranger units, and households.

WTP question format:

When the expanded establishment and maintenance of fire breaks is completed, it is expected to reduce the number of forest burned each year and money loss. Last year, the number of hectares of forests burned in the province was 228 hectares. The loss is estimated about one billion of Vietnam Dong. If the fire break program was carried out, the area of forest burned would reduce on 50%, equivalent to 114 hectares

Suppose that the fire breaks establishment and maintenance program would be implemented from the next year. What is maximum amount would you pay each year to have fire breaks built and maintained in our province.

The study area is mountainous and people living in the area depend mainly on agriculture and forestry. The income comes mainly come from selling products of agricultural and forestry activities. This income is not high compared to the requirements of daily living. Therefore, we decided to show respondents two types of payment card. One is in money and the other is in labor (working days). The payment card in money includes 12 different Vietnam dong (Vietnamese currency) amounts ranging from 0 to 700,000 Vietnam dongs a year. The payment card in labor includes 12 working day amounts ranging from 0 to 30 days a year. The labor amounts were chosen based on the experience that during the war time each laborer (aged from 18 to 60 for the males and from 18 to 55 for the females) had to contribute from 10 to 15 days every year to social work like dam, road or irrigation system construction (Commonly called 202 program). From the range of payments, 0.5 days has been added after pre-test done in the survey place. The money amounts were calculated by multiplying labor amounts to current rate of wage for a working day in the rural area. This rate is estimated in average about 25,000 Vietnam dongs.

Payment card in working days

Working Days/a year	0	0.5	3	6	9	12	15	18	21	24	27	30

Payment card in Vietnamese currency (Vietnam Dong)

VND/a Year (Thousand VN Dong)	0	12.5	75	125	225	300	375	400	525	600	675	700

Finally, there is a series of questions, aimed at knowing understanding of respondents on forest fires, respondents' reaction to the survey and to obtain respondents' socio- economic information.

2.5. Sample selection and implementation

2.5.1. Characteristics of survey area

HoaBinh is a mountainous province locating in the North-West of Vietnam and is about 50 km from capital city HaNoi with population of 789.300 persons and average density of 169 persons/km^2. Total natural area of the province is 466,254 hectares among which forestry area is 174,771 hectares. There are 10 districts and a provincial capital town. Economic structure consists of 49.16 % from agriculture, forestry and fishing, 17.58 from industry and construction, and 33.28% from services. People still depend very much on agriculture and forestry to earn their living.

DaBac district is one of 10 districts in the province. It is about 30 km from HoaBinh provincial capital town. DaBac population is 50,440 persons and its natural area is 82,000 hectares. The sampling frame was households living in 2 communes TuLy and

CaoSon of DaBac district- HoaBinh province. TuLy and CaoSon communes locate closely to TuLy state forest enterprise. We performed a stratified random sample of these households with the strata being DaBac district. The second reason for selecting these two communes is our belief that if CVM does not work in the area close to the forest, then it is even more unlikely to work further away. TuLy and CaoSon communes have 1130 and 730 households respectively. The forest area of TuLy is 70 hectares and 88 hectares is the forest area of CaoSon commune. In-person interviews were used for 70 respondents.

To identify households to be sampled, we selected names of household heads from commune lists for farmers, school teachers from directors of the schools, officers from state forest enterprise. We tried to include different categories of people such as men, women, farmers, school teachers and officers of different ages. The sample drawing is random given the availability of stakeholders.

As we know, CVM has been developed and mostly applied in developed countries. Therefore, the way questions are designed is typically appropriate to these countries. Vietnam is a developing country, thus the questions in the survey are to be understandable to local people. To have this, we revised the questions in the survey after discussing with experienced officers of TuLy State forest enterprise who have worked for a long time with forest fire dealing and the first four interviews. The revision focused on the following questions:

Original questions	**Revised questions**
Q1. Do you think fire breaks would work and ***reduce*** forest fires	Q1. Do you think fire breaks would work and ***prevent*** forest fires
Q2. Do you think ***with fire break established, flooding in rainy reason would be less***	Q2. Do you think ***when fire breaks are established, they would help reduce flooding in rainy reason***

Q3. Do you ***think with fire break established, water would be more available in dry season***	Q3. Do you think ***when fire breaks are established, they would help increase water in dry reason***

Vietnam has been in central planning economy for a long time. The market economy has just been applied by the government for the last 20 years. Therefore, people in most rural areas are accustomed to the reality that government funds all public projects. Officers from TuLy State forest enterprise have warned again on this matter and asked to be ready to explain to farmers that this extended fire break establishment and maintenance program is hypothesized only and served for the research purpose at Vietnam Forestry University. According to these officers, this is very important because the survey could raise an expectation for farmers on possible government funded program. This misunderstanding also could bring a trouble to forest enterprise in future fire prevention activities that involve local people. These officers also suggested that payment cards in working days show to respondents at first. This would help avoid misunderstanding that they have to pay to have the program implemented. With the first four interviews, we have learned income of farmers is really hard to be obtained. This is easily understood because farmers produce nearly everything for themselves and markets. They never keep records on how much they earn every month. Thus, income estimation from farmers is not very accurate. For collecting income of officers, teachers, pensioners we had no difficulties.

Interviews were conducted face to face in the households of the selected individuals. The survey was carried out at any time of the day because selected respondents were busy with their daily job. The respondents showed us a good knowledge and understanding on forest fire and fire breaks, therefore we have not many difficulties in completing the interviews.

Table 7-1 Sample distribution per age and profession categories

Age	Farmer	Forest enterprise officers	Others (teachers, pensioners..)	Total	Percentage
18-29	14	1	7	22	31%
30-44	8	7	4	19	27%
45-60	14	8	3	25	36%
Older	4			4	6%
Total	40	16	14	70	
	57%	23%	20%		100%

2.5.2. Response rate and protest responses

With a small sample of 70 selected individuals and adoption of in-person interview, the response rate of our survey would be high. 100% of contacted respondents have participated in the interview. High response rate could be because of the hospitability and culture of Vietnamese rural people, expectation from the proposed program and curiousness to the interview.

The first five questions focused on understanding of respondents on forest fires and fire breaks. The result of the survey on this matter is illustrated in table 7-2. In table 7-2, 63 respondents answered that fire break would work and prevent forest fires, nobody said no and 7 people answered “don’t know”. These answers indicate that respondents were aware of about fire breaks and concerned about forest fires. 90 % answered yes to question 1 showing a good understanding on function of fire breaks. This is understandable because these respondents are living closely to forests or they could have used or seen fire breaks before. Question 2 asked about ability of fire breaks on helping reduce flooding in rainy season. 95.7% said yes and 4.3% said don’t know to this question. During the survey, we found that flooding happened quite often in the last several years.

Table 7-2 Opinions of respondents on fire breaks

Questions	Vote	Percent
1. Fire breaks would work and prevent forest fires		
Yes	63	90%
No	0	0%
Don't know	7	10%
2. Established fire breaks would help reduce flooding in rainy season		
Yes	67	95.7%
No	0	0%
Don't know	3	4.3%
3. Established fire breaks would help increase water in dry season		
Yes	59	84.3%
No	0	0%
Don't know	11	15.7%
4. Fire breaks should not used because of too much labor		
Agree	1	1.4%
Disagree	32	45.7%
Don't know	37	52.9%
5. Fire breaks would not work to reduce forest fire spread		
Agree	0	0%
Disagree	49	70%
Don't know	21	30%

The reason of this flooding is the loss of forests. People believe that no fires, no loss of forests, then no flooding. We also saw the expectation of local people on potential government funded program on forest fire prevention, thus this could be one of the reasons of high yes saying to question 2. Question 3 was on whether forest fires could help increase water in dry season or not?. 84.3% of respondents said yes and 5.7% said don't know to this question. We have found that local people are more knowledgeable on flooding problem than on water increase in dry season or flooding caused more losses to them than water shortage. Local people now could cultivate only in rainy season. Many respondents wish to have more water to have to more crops a year. This is a reason why respondents put much expectation on fire break establishment and maintenance program. 37 respondents (52.9%) answered don't know on question 4. They raised a question: too much labor is how much?. We believe that ambiguous questions like this should be avoided in future surveys, especially in those surveys that respondents are farmers or people from rural area in developing countries. 45.7% of people said disagree to this question. Question 5 was on testing whether respondents believed fire breaks would work to reduce forest fire spread or not?. 70% of interviewees disagreed with this statement showing that fire breaks look potential in preventing forest fire spread. 30 % of respondents answered don't know to this question. In general, we could see that respondents showed quite good understanding on forest fires and fire breaks. These people have a belief in fire breaks in preventing the forest fire spread. The use of fire breaks would be beneficial to local people in reducing flooding in rainy season and increasing water in dry season.

After willingness to pay question was asked, we put a question on why respondents answered the WTP question as they did. This helps us understand their opinions and point of view on proposed program on fire break establishment and maintenance. Basically, the provided reasons could be grouped as follows:

1. For those people that do not contribute money but labor:

+ They do not have cash, because they are farmers and available cash is not enough for their daily living and schooling

+ They like the program and would work for that.

+ They believe that the proposed program is necessary and would bring benefit to them

+ Other people would agree, and then she or he agrees to contribute to the proposed program

2. For those people who do not contribute labor but money:

+ They are busy with their daily job

+ They are not strong enough to work (pensioners)

After this question, a series of follow-up check questions were asked to determine if those refusing to pay represent a valid representation of their value or reflect a protest about some feature of the WTP question or payment card (Mitchell and Carson, 1989). As shown in appendix 1, the check question had 6 categories plus an 'other' category. The first two categories were "I cannot work because we are too busy with out field job and "My family does not receive any benefits from forests". These statements represent valid reasons for indicating why they would not pay and are not considered to be a protest response against the survey. In our survey, 1.4% of respondents explained that they were too busy with their job and would not contribute anything. The next 4 categories and the last "other" are often classified as protest responses. These include "The program would not work/ not realistic/ use other ways", "Only people living close to forests have to pay", "I do not trust the government program", "Government should pay for that program" and "Other: Please list the reasons". About 2.8% of respondent answers belong to these five protest response.

2.6. Coding the survey

In the survey, we use some questions with 3 options for answering like: 1) yes, 2) no, 3) do not know or 1) agree, 2) disagree, 3) do not know. For the statistical analysis, these answered are coded as follows:

Question 1: Do you think fire breaks would work and prevent forest fires?

______Yes ______No _______Don't know

"Yes" answer is coded as 1

"No" answer is codes as 0

"Don't know" is blank. As mentioned in the sample selection, we chose to do the survey in 2 communes that locate closely to forests. The selected interviewees know quite well forests, forest fires and fire breaks in forests. With the answer "don't know", the respondents seem to be not clear on the function of fire breaks or they just did not want to hurt the proposed program and this is typical reaction of rural people towards the government program in Vietnam. In this situation, we could leave "don't know" blank.

Question 2: Do you think when fire breaks are established, they would help reduce flooding in rainy reason?

______Yes ______No _______Don't know

"Yes" answer is coded as 1

"No" answer is codes as 0

"Don't know" is left blank.

Question 3: Do you think when fire breaks are established, they would help increase water in dry season?

______Yes ______No _______Don't know

"Yes" answer is coded as 1

"No" answer is codes as 0

"Don't know" is left blank.

In Vietnam in the last few years, many dangerous floods occurred in the area where forests have been cut causing a lot of social and environmental problems. These floods were shown on TV, broadcasted on radio and appeared on newspapers. People know quite well flooding in rainy seasons and drought in dry season where forests became degraded and rare. If a respondent says don't know on these two questions, this may show that this respondent does not know much about forest fire and fire breaks. Therefore her or his information on these two questions is lightly weighted. With these reasons, we could leave the answers "don't know" on questions 2 and 3 blank. There are only 12 answers "don't know" among 140 surveys in two questions.

Question 4: Fire breaks should not be used because they require too much labor:

______Agree______disagree _______Don't know

"Agree answer" is coded as 1

"Disagree answer" is coded as 0

"Don't know" answer is left blank. As mentioned above, forests in Vietnam have been cut much and natural forests exist only in very remote mountainous areas. Forests close to residential areas are mainly planted, therefore the terrain is not so complicated and not many bushes in these forests. On technical part, we can use natural barriers such as streams, assess roads, wetlands for establishing fire breaks. Therefore, establishment and maintenance of fire breaks requites not big amount of labor. We believe that who living closely to forests can know this quite well. That's why, we code "don't know" answer as blank.

Question 5: Fire breaks would not work to reduce the spread of forest fires:

______Agree ______Disagree _______Don't know.

"Agree" answer is coded as 1

"Disagree" answer is coded as 0

"Don't know" answer is lef t blank. The function of fire breaks is to prevent the spread of forest fires. Establishment of fire breaks in plantation is a technical requirement. This means that the benefit of fire break in reducing forest fire spread is very clear. The respondent saying "I don't know" on question 5 is not clear about the benefit of forest fires, this means she or he was not clear about the role of fire breaks in reducing the spread of forest fires. Thus, we could leave "don't know" answers blank for question 5.

Question 9: Have you ever seen forest fires?:

Yes___________No____________

"Yes" answer is coded as 1

"No" answer is coded as 0

Question 10: Have forest fires ever disturbed or bothered you?

Yes___________No____________

"Yes" answer is coded as 1

"No" answer is coded as 0

Question 14: Do you own any area of forests?:

Yes___________No____________

"Yes" answer is coded as 1

"No" answer is coded as 0

Question 15: Are you an officer or farmer?

_______Officer_____farmer________other

"Farmer" answer is coded as 1

Officer and other (school teachers, pensioners) answer is coded as 0. This is because officers, school teachers and pensioners are those who receive salary from government budget. Farmers just earn by themselves.

2.7. Model construction

To determine the WTP for the extended fire breaks establishment and maintenance, the survey information is used in estimating linear and tobit regressions. Calculating WTP for HoaBinh province residents using linear and tobit regressions allows for estimating the value of the proposed program in term of labor and money along with impacts of understanding of respondents on forest fire and fire breaks, education and other demographic variable. Initial development of these two regressions begins with the identification of possible significant variables that influence support for the proposed program. Lack of variation in responses in the survey data can create statistical problems like problem of convergence of the model. Therefore, the collected data would form a near singular matrix, thus not allowing for computation. NoReFireSpread, FloodReduce, WaretIncrease FBshouldnotused and FirePrevent variables are excluded, even they seem to be important predictors in the model because they have nearly no variation. Highly correlated variables also are excluded from the initial model. YearLive is correlated to Age and Age was excluded. We believe that YearLive would be more meaningful and would explain the dependent variable more than the Age variable does because many residents moved into the area recently even they are at old ages (40, 50 or 60). Secondly, regression with YearLive gives better statistics in term of t-statistics and R^2. ForestArea correlates to FireInfluence and it was taken out because the regression with ForestArea has weaker statistics. We also could see that one of the purposes of our study is to determine WTP of respondents for fire break establishment and maintenance program, therefore FireInfluence (fire bothers or disturbs local people) would likely be a better explanatory variable than ForestArea. Thirdly, if both ForesArea and FireInfluence variables are included in regression, then the ForestArea has a negative sign. This is not as expected. Income is correlated to Education and Income was eliminated from our regression. We choose Education because Income is not very accurate, especially for farmer.

Table 7-3 Variables of initial model

Variable name	Score given to variable	Definition of variable	Expected sign
I. Dependent variables			
Laborc		Respondents' labor contribution of to have proposed program implemented	
Moneyc		Respondents' money contribution to have proposed program implemented	
II. Independent variables			
FirePrevent	1 Yes, 0 No Don't know	Determines if fire breaks would work and prevent forest fires	+
FloodReduce	1 Yes, 0 No Don't know	Determines if fire breaks would reduce flooding in rainy season	+
WaterIncrease	1 Yes, 0 No Don't know	Determines if fire breaks would increase water in dry season	+
FBShouldnotUsed	1 Agree, 0 Disagree Don't know	Determines whether fire break should not used because they require too much labor	-
NoReFireSpread	1 Agree,0 Disagree Don't know	Determines opinion of respondent on whether fire break would work to reduce fire spread	-
FireSee	1 Yes, 0 No	Dummy variable testing whether a respondent has seen fire or not	+
FireInfluence	1 Yes 0 No	Dummy variable testing whether a respondent has been disturbed or bother by fire or not	+
YearLive	1,2,3...	Number of years a respondent lives in province	+
Age	1,2,3...	Age in years	+
NumberPeople	1,2,3	Number of people in respondent's family	+
ForestArea	1 Yes, 0 No	Dummy variable testing whether a respondent owns any area of forest or not	+
Farmer	1 Farmers 0 Others	Dummy variable determines whether respondent is farmer, officer or others	+
Education	0, 1, 2, 3...	Education range of respondents	+
Income	0, 1, 2, 3...	Income range of respondents' households	+

2.8. Result of regression on WTP

After elimination unusable variables as discussed in *2.7*, we run regression with 2 dependent variables: labor and money contribution. We used OLS for the case with labor dependent variable and tobit regression for the case with money dependent variable. We used tobit regression because we have many zero values of money contribution variable (See appendix 14)

Table 7-4 Results of regression

OLS dependent Variable: LABORC				Tobit dependent Variable: MONEYC			
Variable	Coefficient	t-Statistic	Prob.	Variable	Coefficient	t-Statistic	Prob.
c	-2.8512	-1.0723	0.288	c	-183525	-1.1986	0.230
Education	0.4140	**2.9216****	0.005	Education	10131	1.17324	0.240
Farmer	3.0386	**2.8009****	0.007	Farmer	-102917	-1.3770	0.168
FireInfluence	0.554	0.6580	0.513	FireInfluence	24767	0.49085	0.623
FireSee	0.383	0.2901	0.772	FireSee	-80415	-1.1156	0.264
NumberPeople	0.238	0.6495	0.518	NumberPeople	4469	0.19854	0.842
YearLive	0.031	1.0008	0.321	YearLive	1893	1.11916	0.263
R-square	0.197724			R-square	0.227585		

** Significance at 5% level

The WTP amount depends on socio-economic factors such as education, farmer or not, fire influence, see fire, number of people in the households and number of years living in the area. The higher the education, or fire influence, see fire, number of people in the households and number of years living in the are, the greater the WTP in amount labor, so the signs of estimated coefficients are expected to be positive. Farmers often have more free time, therefore they would contribute more labor to the proposed program than officers, pensioners or school teachers. In term of money contribution, WTP also depends on these socio-economic factors, but we see different signs of coefficients of these variables in table 7-4. Estimated coefficients of farmer and fireSee variables have a negative signs meaning the farmers would pay for the fire break program less than people receiving salary from government. It is obvious that local people are in poor condition and what they produce is just enough for their daily living. Therefore they like to contribute working days to proposed program than money. Looking at t- statistics in table 7-4, farmer and education variables are significant at level of 5% for the case with dependent variable in labor contribution. Thus WTP, in this case, does depend on education and who is the respondent, but not on fireinfluence, firesee, numberpeople and yearlive. As education increases by one level, then the respondent would work 0.41 days more (a half days). If the respondent is a farmer, then WTP would increase 3 days more.

For the money contribution dependent variable, the tobit model has been used. The coefficients of tobit regression are to be interpreted as follows: a change in independent variables has two effects- an effect on mean of dependent variable and an effect on the probability of dependent variable to be observed (McDonald and Moffitt, 1980). For our study, a change in Education, Farmer, FireInfluence, FireSee, NumberPeople, YearLive would change money contribution in two ways: mean of this money contribution above zero (limit) and probability of being observed above zero value. We can use the technique discussed by McDonald and Moffitt (1980) to calculate these two changes of money contribution whenever there is a change in independent variables. However, the results of regression in the case of money dependent variable show insignificance of all variables. Thus, WTP does not depend on any of selected independent variables. The question raised here is whether we should carry out the survey with WTP in money or not in particular fire prevention program in Vietnam and in developing countries like Vietnam as whole?. To answer this question, we create a variable PayMoney from our collected data of 70 surveys for fire break establishment and maintenance program. PayMoney is 1 if respondents agreed to pay money to proposed program and 0 if respondents did not agree to pay money and we use probit model for this binary dependent variable case. Our purpose of using the probit model is to find out the probability of respondents who agreed to pay to proposed bid amount in money.

From table 7-5, we could see that farmer variable is significant at level of 5%. To focus the impact of significant variable "farmer" on dependent variable "paymoney" (pay money or not), we dropped out insignificant independent variables and run regression of paymoney on farmer independent variable only.

Table 7-5 Probit regression for money dependent variable

Dependent Variable: PAYMONEY				
Method: ML - Binary Probit (Quadratic hill climbing)				
Sample(adjusted): 1 70				
Included observations: 63				
Excluded observations: 7 after adjusting endpoints				
Convergence achieved after 5 iterations				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
c	-0.290540	1.523704	-0.190680	0.8488
Education	0.034368	0.081120	0.423670	0.6718
Farmer	-1.352652	0.683650	**-1.978575***	0.0479
Fireinfluence	-0.070489	0.493561	-0.142817	0.8864
Firesee	-0.554778	0.740199	-0.749499	0.4536
Numberpeople	-0.072638	0.234777	-0.309389	0.7570
Yearliev	0.012991	0.017758	0.731570	0.4644
Mean dependent var	0.174603	S.D. dependent var		0.382677
S.E. of regression	0.352270			
Log likelihood	-22.03477			
Restr. log likelihood	-29.17597			
LR statistic (6 df)	14.28240	McFadden R-squared		0.244763
Probability(LR stat)	0.026636			
Obs with Dep=0	52	Total obs		63
Obs with Dep=1	11			

*Significance at 10% level

Table 7-6 Reduced probit regression

Dependent Variable: PAYMONEY				
Method: ML - Binary Probit (Quadratic hill climbing)				
Sample(adjusted): 1 70				
Included observations: 70 after adjusting endpoints				
Convergence achieved after 5 iterations				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
c	-0.372289	0.230863	-1.612595	0.1068
Farmer	-1.260259	0.407359	-3.093732	0.0020
Mean dependent var	0.185714	S.D. dependent var		0.391684
S.E. of regression	0.363686			
Sum squared resid	8.994210			
Log likelihood	-28.05076			
Restr. log likelihood	-33.59640			
LR statistic (1 df)	11.09129	McFadden R-squared		0.165067
Probability(LR stat)	0.000867			
Obs with Dep=0	57	Total obs		70
Obs with Dep=1	13			

The significance of farmer variable shows us that the probability of agree to pay depends on whether the respondent is farmer or not. We could state that Z score of farmer is -1.634 (-0.373-1.261). We can directly translate this Z score into probability with using the standard normal distribution table. The probability that a person is a farmer and agrees to pay to bid amount in money is the probability associated with the Z score -1.645, or 0.0516. That is, if there were such a person, they would have a 5.16% chance of paying the proposed bid amount. Thus, from 100 farmers interviewed, there would be only six farmers that agree to pay to bid amount in money. DacBac district and HoaBinh province (where survey was implemented) is a rural and mountainous one, therefore residents there are mainly farmers. With only 5.16 % of farmers would pay to proposed bid amount in money, we could say that the bid amounts in money are to be taken out of our survey and WTP in money would not be realistic for fire prevention program in DacBac district, HoaBinh province, Vietnam.

2.9. Willingness to pay estimate

2.9.1. Sample WTP estimate

Sample WTP estimate was calculated from the data from question 6 in the survey which asked the respondents how much they would pay for fire break establishment and maintenance. In table 7-7, the sample WTP per household, the mean estimator, is 4.9357 days a year (5 days).

2.9.2. Population WTP estimate

The total population WTP can be inferred from the total sample WTP, which is a product of the sample WTP mean and total households of population of the district and province. The total number of households of DaBac district is 9,618 and total number of households of HoaBinh province is 132,215. The total WTP per year of DaBac district is 48,090 working days and the total WTP of HoaBinh province is 661,075 working days in a year.

Table 7-7 Statistical descriptions for sample WTP with labor contribution

Items	LABORC (working days)
Mean	4.935714
Median	6.000000
Maximum	15.00000
Minimum	0.000000
Std. Dev.	2.924065
Skewness	0.500183
Kurtosis	3.986513
Jarque-Bera	5.757324
Probability	0.056210
Observations	70

3. CONCLUSION AND POLICY IMPLICATION

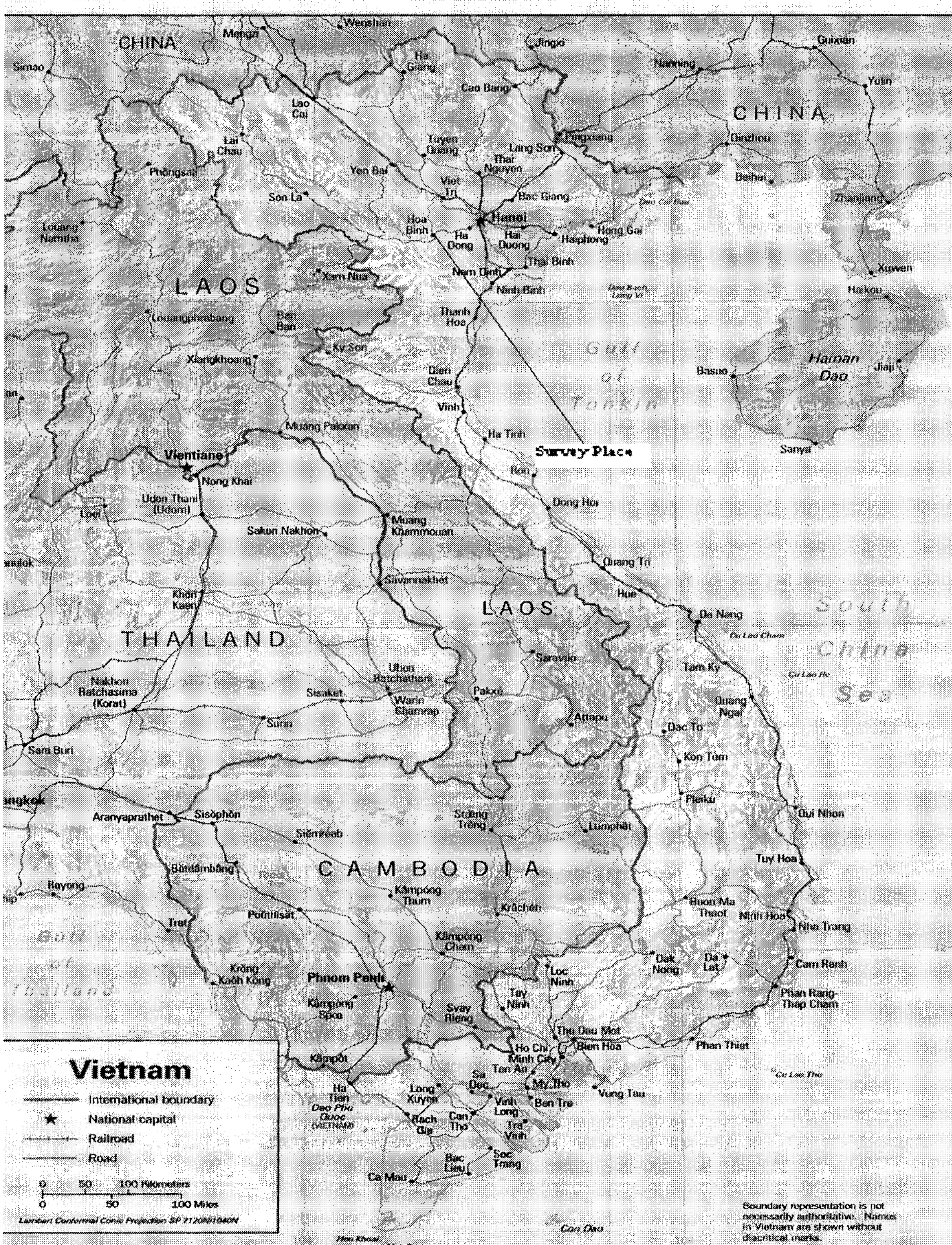
This study shows that local people in forest area are concerned about forest fires and forest fire prevention program. All most interviewees (90%) believed that fire breaks would work to prevent forest fires. 96% of respondents were confident in the fact that fire breaks would reduce flooding in rainy season and 84.3% thought with fire breaks established, water in dry season would be increased. It appears that CVM works for this fire prevention program. However, during the survey designing process, attention should be paid to local factors such as income of local people, expectation in real program from local people, and level of literacy of respondents. Question in the survey should be specific, wording is to be simple and understandable to local people, and vague questions should not be asked. An interesting result from this study regards the type of payment. In developed countries, payments often are offered in money, but payments should be more flexible for developing countries including Vietnam. In this study, we found that payment in working days were used and accepted by local people, and payment in money was found unrealistic for fire break establishment and maintenance program. The study results from CVM application show that the household mean WTP for fire break establishment and maintenance is 5 days a year. Based on this study, the authors estimate that total WTP per year of DaBac district is 48,090 working days and the total WTP of HoaBinh province is 661,075 working days in a year.

This study has yielded a working labor estimate of benefit gained in HoaBinh province of Vietnam for implementation of fire prevention program. It is very substantial. This is a compelling piece of information not typically available to policy makers, managers, especially in developing countries, when a positive externality, for which there is no market, is involved. This benefit is not small to a province of Vietnam from local people. This research result will benefit policy makers, researchers in changing policies and practices for forest management as whole and forest fire control in particular. Traditionally, in Vietnam sources for forest fire control come from government. Therefore, these sources are in short and ineffectively used. Working days from local people contributed to fire prevention will be an important addition besides sources from government.

The quantitative estimates developed in this study are central to the formulation and implementation of credible and defensible policies for protection of forests in HoaBinh province and in whole Vietnam. Given the fact that forest protection is a public good without a traditional market, the application of revealed preference techniques such as the travel cost method to estimate the benefit of forest protection is clearly not feasible. Thus, the value of CVM lies in the fact that this method enables the estimation of an approximate labor value via stated preferences of the affected parties or stakeholders.

The labor value found in this study could be used for determining responsibility share of each household for forest protection program. Five working days a year is a preliminary suggestion for policy makers and managers in selecting a norm for social work. Application of CVM is very rare in developing countries and, therefore lessons learned from this study are of special value to researchers and policy makers.

Survey Place



Survey place in Vietnam Figure 5

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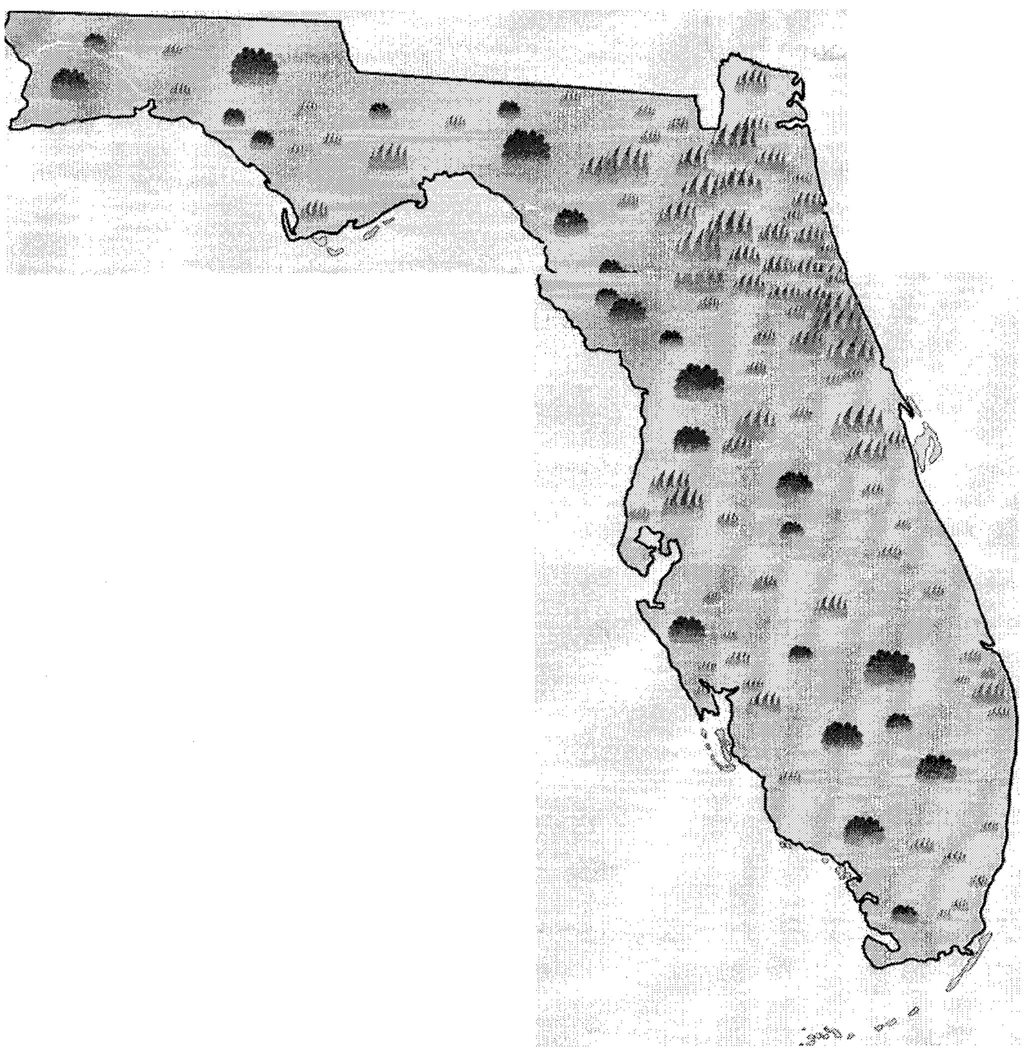
APPENDIXES

APPENDIX 1: Surveys in three states of USA and Vietnam

EXPANDED FLORIDA FIRE MANAGEMENT PROGRAM



What do you think?

EXPANDED FLORIDA FIRE Management PROGRAM

What do you think?

Expanded Florida Fire Management Program

DEFINITIONS:

Fire in Florida is an ever-present and natural part of the landscape. Your views on this topic are very important to Florida fire managers as they decide how to protect houses and preserve Florida's forests and wildlife in the future. Your participation in this survey is greatly appreciated. Please read the booklet over prior to your scheduled phone interview. This will speed up your interview. Thanks.

Before you answer this survey we want to familiarize you with the following fire management terms:

Prescribed Fire or prescribed burn: A fire purposely set in a designated area to accomplish one or more specific objectives such as removal of underbrush and dead wood to reduce available fire fuel and increase the ability to control future wildfires.

Wildfire: A fire started by human activities or a lightning strike. A wildfire, occurring under unfavorable weather conditions, can be difficult to control due to high intensity and/or rapid rate of spread.

Fire management: Consists of the following four activities: fire prevention, prescribed burning, fire detection and fire suppression.

Structural fire: A building or house that is on fire.

Health standard: The minimum level of air quality which the Environmental Protection Agency considers to be healthy. Before beginning let me tell you that currently the Florida Division of Forestry has in place a fire management program that both controls wildfires and authorizes prescribed fire on federal, state and private forest and rangelands in Florida.

DESCRIPTION

What Is The Current Problem?

An attempt to keep fire from burning forest and rangelands over the past several decades has helped lead to an unnatural build up of wildfire fuel in the form of brush, dead branches, logs and pine needles on the forest floor. Generally, resulting wildfires burn very hot. As shown in Figure 1 flames from these wildfires burn all the way to the top of tall trees and houses and spread very fast making these wildfires difficult to put out. Under very dry conditions these high intensity wildfires burn nearly everything, frequently causing the high levels of air pollution shown in Figure 1.

WILDFIRE

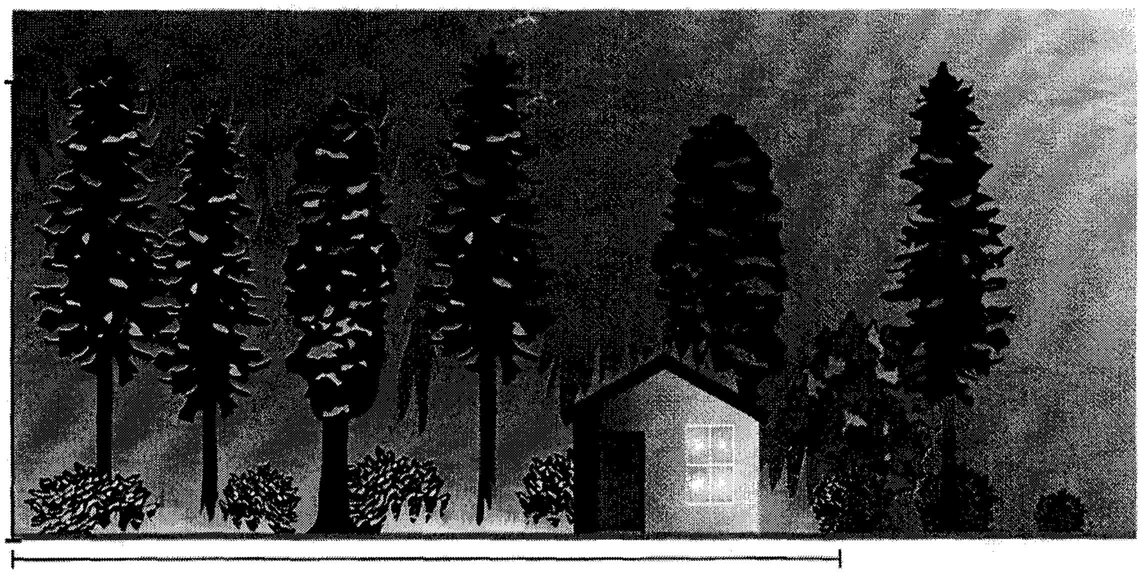


Figure 1

Fire spread 1/2-2 miles / hour

What Is A Solution?

One long term solution to the problems caused by unnatural build-up of wildfire fuel is to restore a fire cycle similar to that which existed historically in Florida.
This means having fire professionals periodically set prescribed fires to clear the forest floor of the excess brush, dead branches and pine needles.

How Does It Work?

These prescribed fires are easier to manage than wildfires since, as shown in Figure 2, prescribed fires do not burn as intensely and they can be directed away from structures. While prescribed fires do result in an increase in air pollution, they generally produce far less air pollution than would a wildfire on the same acreage.

Most importantly, fire professionals reviewing the 1998 Florida wildfires suggested that areas that had been previously prescribed burned, tended to have lower flame lengths and slower rates of spread. This slower rate of spread and lower flame length often made it possible to contain wildfires and protect structures which would have otherwise been lost.

Studies by the Florida Division of Forestry and the USDA Forest Service indicate that under normal weather conditions prescribed burning reduces the number of acres that would burn each year from wildfires.

PRESCRIBED BURNING

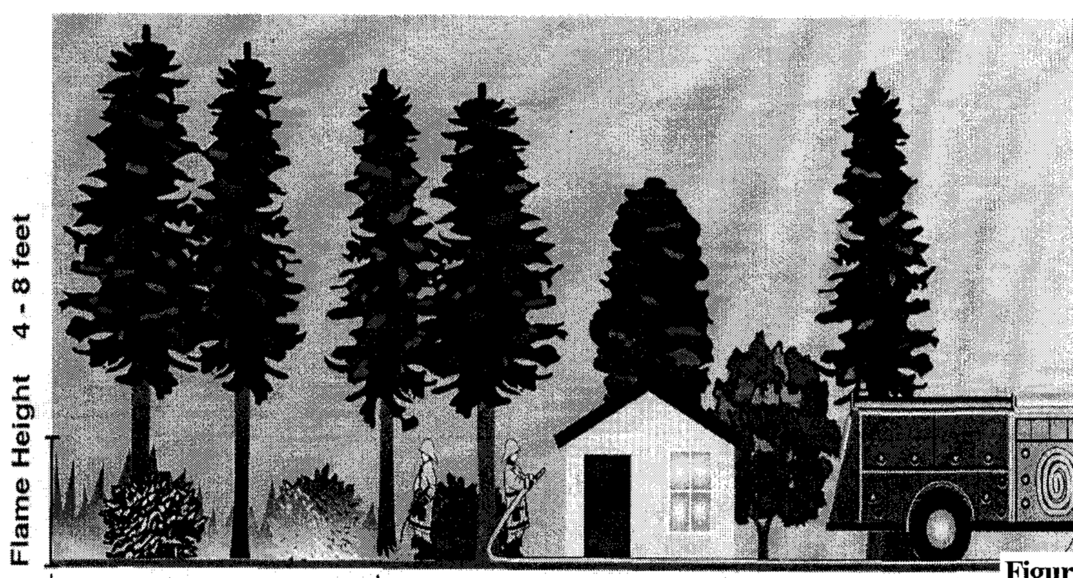


Figure 2

Fire spread 60-120 feet / hour

What About Air Quality?
By timing prescribed fires with favorable weather and wind conditions, smoke can be directed away from the majority of the population. As seen in Figure 1, wildfires generally produce more smoke than prescribed fires, and wildfire smoke can exceed health standards.

What Is The Proposed Program?
Foresters and fire professionals have developed an expanded program of prescribed burning on Florida's 28 million acres of federal, state and private forest and rangelands to reduce the extent and damages of wildfires. Under the current program, about 1.4 million acres is prescribed burned each year.

To reduce the size and damage from wildfires, and to improve the safety of both the public and firefighters, it is recommended that 1.9 million acres be prescribed burned each year.

Features Of The Program
This Expanded Florida Prescribed Burning Program is believed by foresters and fire professionals to be the minimum sufficient to:

- restore a fire cycle similar to that which existed historically in Florida by increasing the frequency of low intensity fires over time, and reduce the threat of high intensity wildfires that could completely burn the forests to the ground and spread to any nearby houses or structures.
- benefit many of Florida's native plant and wildlife species. For example, prescribed fire allows sunlight to reach the forest floor which stimulates the growth of many types of flowers and shrubs thereby providing food sources for wildlife.
- reduce the chances of wildfire smoke exceeding air quality health standards
- control forest diseases.
- protect wildlife due to the slow moving nature of prescribed burns which allows wild animals to find refuge in damp areas or migrate out of the area.

Results Of The Program

If the Prescribed Burning Program is expanded in Florida, it is expected to reduce the number of acres of high intensity wildfire and houses lost to wildfires. Currently, in a typical year approximately 5,300 wildfires burn approximately 200,000 acres and destroy about 43 houses in Florida. If the Expanded Florida Prescribed Burning program were implemented it is expected to reduce the number of acres burned by wildfires from approximately 200,000 acres burned to about 150,000 acres for a total reduction of 50,000 acres. This represents a 25% decrease in acres burned by wildfire. The number of houses destroyed by future wildfires is expected to be reduced from an average of 43 a year to about 25.

Given the discussion above, do you think forest managers should or should not undertake this program of prescribed burning underbrush and debris in pine forest?

1. Should
2. Should not
3. Don't know

Costs of the Expanded Florida Prescribed Burning Program

While prescribed burning programs such as described above have proven effective at reducing the extent and severity of wildfire, there is not sufficient funding currently available to carry out such programs on all of the 28 million acres of federal, state and private forest and rangelands in Florida.

Who Would Fund This Program?

The State of Florida is considering using some of the state revenue as matching funds to help counties finance fire prevention programs. If a majority of residents vote to pay the county share of this program, the Expanded Florida Prescribed Burning Program would be implemented in your county and other counties in Florida on state forest and rangelands and willing private land owners.

Funding of the Expanded Florida Prescribed Burning Program would require that all users of Florida's forest and rangelands, such as timber companies, recreation visitors, and Florida households pay the additional cost of this program. If this expanded program were to be implemented, by law, the money would be deposited in a separate Florida Prescribed Burning Fund which could only be used to carry out the prescribed burning program described above. A citizen advisory board would review the expenditures from the fund annually.

Results of the Program

If the Expanded Prescribed Burning Program was undertaken it is expected to reduce the number of acres of wildfires shown in Figure 1 from the current average of approximately 200,000 acres each year to about 150,000 acres, for a 25% reduction. The number of houses destroyed by wildfires is expected to be reduced from an average of 43 a year to about 25.

Your Chance to Vote

Your share of the Expanded Prescribed Burning Program would cost your household $ ______ a year. If the Expanded Florida Prescribed Burning Program were on the next ballot would you vote

1. In favor
2. Against

Mechanical Fire Fuel Reduction Program

Another approach to reducing the build up of fuels in the forest is to "mow" or mechanically chop the low and medium height palms and bushes into mulch. This is especially effective at lowering the height of the vegetation, which reduces the ability of fire to climb from the ground to the top or crown of the trees. In addition, mechanical "mowing" slows the new vegetation growth with the layer of mulch acting as a barrier.

Mowing or mulching 1.9 million acres of forest and rangelands is more expensive than prescribed burning, due to increased labor and equipment needs. It would also decrease the number of ground cover plant species reducing food for wildlife. However, unlike prescribed burning, mulching does not produce any fire smoke.

Results of the Program

If the Mechanical Fire Fuel Reduction Program was undertaken instead of the Expanded Prescribed Burning Program, it is expected to reduce the number of acres of wildfires shown in Figure 1 from the current average of approximately 200,000 acres each year to about 150,000 acres, for a 25% reduction. The number of houses destroyed by wildfires is expected to be reduced from 43 a year to about 25.

Your Chance To Vote

Your share of this Mechanical Fire Fuel Reduction Program would cost your household $ ________ a year. If the Mechanical Fire Fuel Reduction program was the **only** program on the next ballot would you vote

1. In favor
2. Against

Herbicide Fire Fuel Reduction Program

Instead of prescribed burning or mowing, a third approach to reduce the build up of fuels in forest and rangelands is to treat vegetation with Government approved herbicides which are nontoxic to wildlife and humans. The application of herbicides, such as weed killer, with a tractor mounted sprayer would eliminate the growth of unwanted vegetation reducing the available fire fuel. This is a common practice in commercial forests in Florida.

While spraying 1.9 million acres with herbicides would be less expensive than mechanically mowing, it would be more expensive than prescribed fire.

Similar to the mechanical treatment, applying herbicides would decrease the number of ground cover plant species reducing food for wildlife. However, it would not produce any fire smoke either.

Results of the Herbicide Fire Fuel Reduction Program

If the Herbicide Fire Fuel Reduction Program was undertaken it is expected to reduce the number of acres of wildfires shown in Figure 1 from the current average of approximately 200,000 acres each year to 150,000 acres, for a 25% reduction. The number of houses destroyed by wildfires is expected to be reduced from an average of 43 a year to about 25.

Your Chance To Vote

Your share of the Herbicides Fire Fuel Reduction Program would cost your household $______ a year. If the Herbicide

Fire Fuel Reduction Program was the **<u>only</u>** program on the next ballot would you vote

1. In favor
2. Against

Demographics

These last few questions will help us understand how well our sample represents the State of Florida. Your answers are strictly confidential and will be used only for statistical purposes. You will not be identified in any way and your name or address will not be distributed or sold to any mailing list.

1. Have you ever been in or personally witnessed what you would consider a wildfire?

1. Yes 2. No

2. Have you ever experienced smoke from a wildfire or prescribed burn?

1. Yes 2. No

//Yes, did it bother you?

1. Yes 2. No

If *Yes, did it bother you... 1. Visually, 2. Physically or, 3. Both*

3. Do you suffer from respiratory or breathing problems?

1. Yes 2. No

If yes, is t a 1. Serious 2. Moderate, or 3. Minor Problem

4. Has your home ever burned or sustained structural damage from a wildfire?

1. Yes 2. No

Yes (# of Times) ____________

5. Has one or more of your nei homes ever burned due to wildfir 12. Ho

1. Yes 2. No

Yes (# of Times) ____________

6. Have you had to evacuate your home one or more times due to wildfire?

Yes (# of Times).

7. What county do you live in?

(Name of County)

8. How long have you lived in this county? ____________ # of years

9. What is your zip code here in Florida

10. Was your zip the same in June 1998?

1. Yes 2. No

If *No, what was your zip in June 1998*

11. Have you lived in other counties in Florida?

1. Yes 2. No

Yes (List Counties) ____________

H w long have you lived in Florida? # Years

Thank you for completing this survey. If you have any comments for us concerning this topic please feel free to express them with your interviewer.

Questionnaire for Vietnam interview

(For in-person interviews)

Good morning/good afternoon/good evening. My name is…. I am from Forestry University- Xuan Mai- Ha Tay. We are doing a study on how to manage our forests better and we interviewing a sample households in the area on this topics.

(Pause)

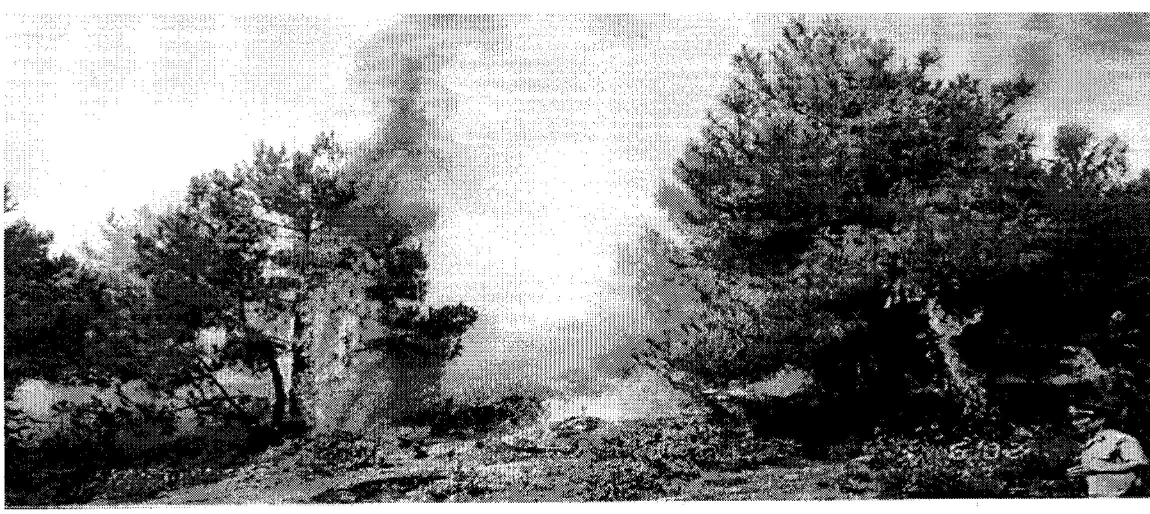
Most of questions are about the attitudes and opinions of the households. There are no wrong or right answers. Completing the survey does not require any special education or skills. All material is read and explained carefully.

(Pause)

Your answers are strictly confidential. The collected data will only be used for study at our university. Your answers will not be reported to anywhere else. Please think carefully about each question and give your honest answer.

What are the current forestry problems in province?

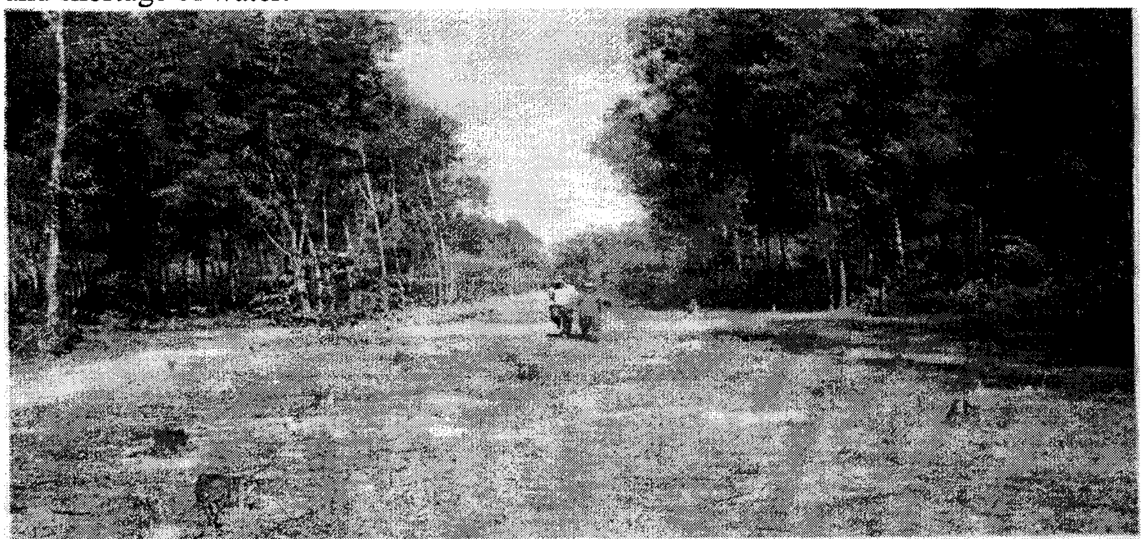
According to statistics of Forest Ranger Department of our province, last year total area of forests was burned is 228 hectares (one hectare is 10.000 m^2), the loss is estimated about 1 billion of Vietnam Dongs. The fires burned nearly everything influencing on surrounding habitat and wildlife. Forest fires are very hot and burn at high density. It is really difficult to put out these fires. Beside the money loss, forest fires also lead to flooding in rainy season and shortage of water in dry season as you have seen.



Forest fires

What is a solution?

One of the solutions to reduce these hot forest fires is to establish fire breaks in forests. This means that in forests at certain distances we construct bands or strips without trees. The width of bands is 1 and half of the height of trees. The distance between bands depends on terrain of forests. We can use natural barriers such as streams, assess roads, wetlands for establishing fire breaks. Then forests will be divided into plots surrounding by bare bands. These breaks would stop fires as planned. Scientists have pointed out that establishing fire breaks is one of requirements in forest plantation and one of effective measures in forest protection. With fire breaks in place, there is fewer chances of forest fires, and thus fewer chances of post fire consequences such as flooding and shortage of water.



• Duờng băng cản lửa rộng 20 m

What is the proposed program?

From Forest Ranger Department of our province, the total forest area at present is 167320 hectares. As suggested by scientists, managers and experienced foresters, there should be an extended program for establishment and maintenance work of fire breaks for current area of forests in the province. It is recommended that every year, fire breaks are to be established and maintained on the area of 30,000 hectares (Total 75 km of fire breaks established).

The benefits of the program are as follows:

- Protection of existing forests, reduction of flooding in rainy season and increase water supply in dry season.
- Quicker access to control fires in large tracts of forested land
- Greater protection to residential areas in wooded areas.
- Increased wildlife habitat diversity with open space in wooded area
- Can be used as access roads for timber harvesting operations.

Now, I would like to ask you some questions about fire breaks in our province.

1. Do you think fire breaks would work and prevent forest fires?
   ______Yes ______No _______Don't know
2. Do you think when fire breaks are established, they would help reduce flooding in rainy reason?
   ______Yes ______No _______Don't know
3. Do you think when fire breaks are established, they would help increase water in dry season?
   ______Yes ______No _______Don't know

Do you agree or disagree with the following statements:

4. Fire breaks should not be used because they require too much labor:
   ______Agree______disagree _______Don't know
5. Fire breaks would not work to reduce the spread of forest fires:
   ______Agree ______Disagree _______Don't know.

Now, let me tell about the results of the program.

When the expanded establishment and maintenance of fire breaks are completed, it is expected to reduce the number of hectares of forest burned each year and loss to wildlife and residential houses in the wooded area. Last year, the number of hectares of forests burned in the province was 228 hectares. The loss is estimated about one billion of Vietnam Dong. If the fire break program was carried out, the area of forest burned would reduce on 50%, equivalent to 114 hectares.

Let's discuss on the cost of making and maintaining the fire breaks.

We could see that the program is effective at reducing forest fires. With less area burned by forest fires, water would be more available in dry season and not as much flooding in the rainy season that destroys crops, houses and other things in the province. However, at present there is not sufficient funding to carry out the proposed program on all forests in our province.

Then who would provide funding to this program?.

The Department of Forest Ranger and provincial authority is considering some sources of finance to help our province forest fire prevention program on the existing forest area. Besides the money from Department of Forest ranger and provincial authority, local residents also have to contribute their part to implementation of the program. With these sources, the proposed program would be completed on forest area in the province.

The resources for expanded establishment and maintenance of fire breaks would require that all users of the province forests including forest enterprises, forest rangers stations, and households contribute the additional money and available resources for this program. If the program were implemented, by Vietnamese law, the money would be put in a separately managed fund which can be used only to carry out the above proposed program. The board of fund body is selected from local people and would review expenditure from the fund annually or when it is necessary.

6. Suppose that the fire breaks establishment and maintenance program would be implemented from the next year. What is the maximum amount of days you would work each year to build and maintain fire breaks in our province

The first card is showed afterward.

Working Day/a year	0	0.5	3	6	9	12	15	16	21	24	27	30

Another to make these firebreaks is to have local people pay to construct them. So instead of working, what is maximum amount would you pay each year to have fire breaks built and maintained in our province

The second payment card to be showed to respondents.

VND/a Year (Thousand VN Dong)	0	12.5	75	125	225	300	375	400	525	600	675	700

7. We are interested in why you answered question 6 as you did. Please tell us why you decided that way?.

____
____
____
____
____

8. If you would not pay anything we would like to know your reasons.
Why was your amount zero?.
- I cannot work because we are too busy with out field job.
- My house does not receive any benefits from forests
- The program would not work/ not realistic/ use other ways
- Only people living close to forests have to pay
- I do not trust the government program
- Government should pay for that program
- Other: Please list the reasons:

____
____

The last few questions will help us understand how well our sample represents the provincial population. Your answers are strictly confidential and used just for statistical purpose in our study, neither your identity nor answers will be shown to anyone else.

9. Have you ever seen forest fires?:
Yes__________No___________
10. Have forest fires ever disturbed or bothered you?
Yes__________No___________
11. How long have you lived in this province? ____________________ Years
12. What is your age?: __________________ Years
13. How many people in your family?:___ Persons (Adults____Children_____)
14. Do you own any area of forests?: Yes__________No___________
15. Are you an officer or farmer?_______Officer_____farmer________other
16. What is your highest school year? Please pick one
0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17
(13: Vocational and technical school, 14: College, 15: Master, 16: Ph. D, 17: Higher (Post doctoral or senior positions))
17. What is an approximate total amount of annual income in your household?
Please choose one of the followings:

Less than 5 million of VN D,	From 5 to 10 million of VN D
From 10 to 15 million of VN D,	From 15 to 20 million of VN D
From 20 to 30 million of VN D,	From 30 to 40 million of VN D
From 40 to 60 million of VN D,	From 60 to 80 million of VN D
From 80 to 100 million of VN D,	And more than 100 million of VN D

Thank you very much for your time and sharing with us your opinions.
Do you have any comments for us?.

APPENDIX 2: **Three state pooled data regressions for 2 programs with state variables** (Protest responses included)

RX program without income variable for the Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/08/04 Time: 22:54
Sample(adjusted): 2 785
Included observations: 644
Excluded observations: 140 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.331563	0.729833	1.824476	0.0681
AGE	-0.005593	0.005898	-0.948283	0.3430
CASTATE	0.918852	0.384399	2.390362	0.0168
CASTATERXBID	-0.001122	0.001634	-0.686886	0.4922
EDUC	-0.025026	0.043628	-0.573623	0.5662
EXPSMOKE	0.096782	0.275630	0.351130	0.7255
FLSTATE	0.779014	0.315751	2.467179	0.0136
FLSTATERXBID	-0.002648	0.001648	-1.607145	0.1080
OWNHOME	0.104074	0.241052	0.431748	0.6659
RESPPROB	0.311235	0.225412	1.380735	0.1674
RXBID	-0.003537	0.000958	-3.690152	0.0002
WITNESSFIRE	0.020422	0.222491	0.091790	0.9269

Mean dependent var	0.684783	S.D. dependent var	0.464964
S.E. of regression	0.445875	Akaike info criterion	1.183731
Sum squared resid	125.6444	Schwarz criterion	1.266980
Log likelihood	-369.1614	Hannan-Quinn criter.	1.216035
Restr. log likelihood	-401.3484	Avg. log likelihood	-0.573232
LR statistic (11 df)	64.37391	McFadden R-squared	0.080197
Probability(LR stat)	1.41E-09		
Obs with Dep=0	203	Total obs	644
Obs with Dep=1	441		

RX program with income variable for the Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/08/04 Time: 22:52
Sample(adjusted): 2 785
Included observations: 583
Excluded observations: 201 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.679250	0.775729	2.164737	0.0304
AGE	-0.003950	0.006413	-0.615967	0.5379
CASTATE	0.944156	0.406392	2.323263	0.0202
CASTATERXBID	-0.001479	0.001714	-0.862650	0.3883
EDUC	-0.051840	0.047727	-1.086167	0.2774
EXPSMOKE	0.024921	0.299931	0.083090	0.9338
FLSTATE	0.642105	0.330311	1.943942	0.0519
FLSTATERXBID	-0.001552	0.001803	-0.860958	0.3893
INCOME	2.74E-06	3.07E-06	0.891309	0.3728
OWNHOME	0.046857	0.265679	0.176365	0.8600
RESPPROB	0.265126	0.235631	1.125175	0.2605
RXBID	-0.003583	0.000991	-3.613799	0.0003
WITNESSFIRE	-0.025946	0.235221	-0.110305	0.9122

Mean dependent var	0.689537	S.D. dependent var	0.463081
S.E. of regression	0.445812	Akaike info criterion	1.188240
Sum squared resid	113.2864	Schwarz criterion	1.285644
Log likelihood	-333.3721	Hannan-Quinn criter.	1.226206
Restr. log likelihood	-361.1514	Avg. log likelihood	-0.571822
LR statistic (12 df)	55.55868	McFadden R-squared	0.076919
Probability(LR stat)	1.44E-07		
Obs with Dep=0	181	Total obs	583
Obs with Dep=1	402		

Mech program without income variable for the Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/08/04 Time: 23:08
Sample(adjusted): 1 785
Included observations: 743
Excluded observations: 42 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.022510	0.632921	-0.035565	0.9716
AGE	-0.000567	0.004952	-0.114580	0.9088
CASTATE	0.160115	0.313755	0.510318	0.6098
CASTATEMECHBID	0.002000	0.001520	1.316387	0.1880
EDUC	0.024506	0.037464	0.654127	0.5130
EXPSMOKE	-0.268941	0.238623	-1.127054	0.2597
FLSTATE	0.428752	0.269735	1.589528	0.1119
FLSTATEMECHBID	-0.001833	0.001638	-1.119365	0.2630
OWNHOME	-0.139368	0.201744	-0.690813	0.4897
RESPPROB	0.120281	0.189686	0.634105	0.5260
MECHBID	-0.003304	0.001009	-3.274120	0.0011
WITNESSFIRE	-0.154963	0.189364	-0.818335	0.4132

Mean dependent var	0.413190	S.D. dependent var	0.492738
S.E. of regression	0.481281	Akaike info criterion	1.327193
Sum squared resid	169.3223	Schwarz criterion	1.401659
Log likelihood	-481.0521	Hannan-Quinn criter.	1.355899
Restr. log likelihood	-503.7529	Avg. log likelihood	-0.647446
LR statistic (11 df)	45.40162	McFadden R-squared	0.045063
Probability(LR stat)	4.12E-06		
Obs with Dep=0	436	Total obs	743
Obs with Dep=1	307		

Mech program with income variable for the Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/08/04 Time: 23:10
Sample(adjusted): 1 785
Included observations: 673
Excluded observations: 112 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.246708	0.672980	0.366591	0.7139
AGE	0.004000	0.005423	0.737613	0.4607
CASTATE	0.111607	0.329488	0.338729	0.7348
CASTATEMECHBID	0.001759	0.001575	1.116944	0.2640
EDUC	-0.014390	0.040829	-0.352438	0.7245
EXPSMOKE	-0.376269	0.254481	-1.478575	0.1393
FLSTATE	0.312801	0.284083	1.101087	0.2709
FLSTATEMECHBID	-0.000767	0.001739	-0.441071	0.6592
INCOME	5.62E-06	2.54E-06	2.207727	0.0273
OWNHOME	-0.242329	0.223389	-1.084786	0.2780
RESPPROB	0.109189	0.198663	0.549616	0.5826
MECHBID	-0.003294	0.001038	-3.174453	0.0015
WITNESSFIRE	-0.157402	0.199859	-0.787565	0.4310

Mean dependent var	0.421991	S.D. dependent var	0.494244
S.E. of regression	0.482650	Akaike info criterion	1.336655
Sum squared resid	153.7475	Schwarz criterion	1.423807
Log likelihood	-436.7846	Hannan-Quinn criter.	1.370406
Restr. log likelihood	-458.2636	Avg. log likelihood	-0.649011
LR statistic (12 df)	42.95800	McFadden R-squared	0.046870
Probability(LR stat)	2.30E-05		
Obs with Dep=0	389	Total obs	673
Obs with Dep=1	284		

RX program without income variable for the Hispanics

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/08/04 Time: 23:00
Sample(adjusted): 1 648
Included observations: 534
Excluded observations: 114 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.246400	0.881392	3.683262	0.0002
AGE	-0.007855	0.007063	-1.112217	0.2660
CASTATE	0.380646	0.343708	1.107469	0.2681
CASTATERXBID	0.002079	0.001619	1.283771	0.1992
EDUC	-0.114039	0.054040	-2.110261	0.0348
EXPSMOKE	0.387851	0.253570	1.529564	0.1261
OWNHOME	-0.383797	0.241041	-1.592250	0.1113
RESPPROB	-0.032390	0.278842	-0.116158	0.9075
RXBID	-0.003913	0.001209	-3.235305	0.0012
WITNESSFIRE	0.007045	0.259194	0.027180	0.9783

Mean dependent var	0.749064	S.D. dependent var	0.433958
S.E. of regression	0.420511	Akaike info criterion	1.084752
Sum squared resid	92.65858	Schwarz criterion	1.164909
Log likelihood	-279.6288	Hannan-Quinn criter.	1.116117
Restr. log likelihood	-300.8350	Avg. log likelihood	-0.523649
LR statistic (9 df)	42.41240	McFadden R-squared	0.070491
Probability(LR stat)	2.76E-06		
Obs with Dep=0	134	Total obs	534
Obs with Dep=1	400		

RX program with income variable for the Hispanics

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/08/04 Time: 23:04
Sample(adjusted): 1 588
Included observations: 478
Excluded observations: 110 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.773610	0.929111	2.985230	0.0028
AGE	-0.007328	0.007732	-0.947757	0.3433
CASTATE	0.616545	0.360819	1.708740	0.0875
CASTATERXBID	0.002040	0.001705	1.196780	0.2314
EDUC	-0.087176	0.059003	-1.477498	0.1395
EXPSMOKE	0.279184	0.265606	1.051118	0.2932
INCOME	-4.61E-06	4.68E-06	-0.985172	0.3245
OWNHOME	-0.232956	0.258551	-0.901006	0.3676
RESPPROB	-0.088988	0.291670	-0.305098	0.7603
RXBID	-0.003885	0.001290	-3.012167	0.0026
WITNESSFIRE	0.168109	0.275250	0.610748	0.5414

Mean dependent var	0.742678	S.D. dependent var	0.437616
S.E. of regression	0.421985	Akaike info criterion	1.094613
Sum squared resid	83.15929	Schwarz criterion	1.190566
Log likelihood	-250.6124	Hannan-Quinn criter.	1.132336
Restr. log likelihood	-272.5734	Avg. log likelihood	-0.524294
LR statistic (10 df)	43.92209	McFadden R-squared	0.080569
Probability(LR stat)	3.40E-06		
Obs with Dep=0	123	Total obs	478
Obs with Dep=1	355		

Mech program without income variable for the Hispanics

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/08/04 Time: 23:20
Sample(adjusted): 1 650
Included observations: 577
Excluded observations: 73 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.028050	0.762967	3.968784	0.0001
AGE	0.000545	0.006136	0.088817	0.9292
CASTATE	0.195297	0.286473	0.681728	0.4954
CASTATEMECHBID	0.001786	0.001370	1.303301	0.1925
EDUC	-0.203269	0.046996	-4.325198	0.0000
EXPSMOKE	0.215109	0.210635	1.021243	0.3071
OWNHOME	-0.028719	0.198388	-0.144760	0.8849
RESPPROB	-0.131904	0.234612	-0.562221	0.5740
MECHBID	-0.002046	0.001067	-1.916873	0.0553
WITNESSFIRE	0.037789	0.216895	0.174228	0.8617

Mean dependent var	0.589255	S.D. dependent var	0.492396
S.E. of regression	0.477609	Akaike info criterion	1.310890
Sum squared resid	129.3387	Schwarz criterion	1.386416
Log likelihood	-368.1918	Hannan-Quinn criter.	1.340342
Restr. log likelihood	-390.7032	Avg. log likelihood	-0.638114
LR statistic (9 df)	45.02282	McFadden R-squared	0.057618
Probability(LR stat)	9.14E-07		

Obs with Dep=0	237	Total obs	577
Obs with Dep=1	340		

Mech program with income variable for the Hispanics

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/08/04 Time: 23:21
Sample(adjusted): 1 588
Included observations: 516
Excluded observations: 72 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.693142	0.806708	3.338433	0.0008
AGE	-0.000568	0.006680	-0.084980	0.9323
CASTATE	0.341753	0.303340	1.126634	0.2599
CASTATEMECHBID	0.001687	0.001461	1.154160	0.2484
EDUC	-0.178165	0.050959	-3.496235	0.0005
EXPSMOKE	0.094289	0.220640	0.427341	0.6691
INCOME	9.87E-07	4.00E-06	0.246912	0.8050
OWNHOME	-0.092798	0.216623	-0.428386	0.6684
RESPPROB	-0.230196	0.248708	-0.925567	0.3547
MECHBID	-0.002229	0.001172	-1.901074	0.0573
WITNESSFIRE	0.135734	0.230088	0.589923	0.5552

Mean dependent var	0.581395	S.D. dependent var	0.493809
S.E. of regression	0.478186	Akaike info criterion	1.317545
Sum squared resid	115.4743	Schwarz criterion	1.408063
Log likelihood	-328.9267	Hannan-Quinn criter.	1.353017
Restr. log likelihood	-350.7962	Avg. log likelihood	-0.637455
LR statistic (10 df)	43.73896	McFadden R-squared	0.062342
Probability(LR stat)	3.67E-06		

Obs with Dep=0	216	Total obs	516
Obs with Dep=1	300		

APPENDIX 3: **Regressions for 2 programs for white and Hispanic people in each state** (protest responses included)

RX program without income variable for the CA Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 12:11
Sample(adjusted): 2 187
Included observations: 160
Excluded observations: 26 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.674528	1.387182	0.486258	0.6268
AGE	0.002716	0.012908	0.210440	0.8333
EDUC	0.053657	0.084905	0.631962	0.5274
EXPSMOKE	-0.294403	0.469845	-0.626597	0.5309
RXBID	-0.004637	0.001346	-3.444267	0.0006
OWNHOME	0.030210	0.478661	0.063114	0.9497
RESPPROB	0.213783	0.520482	0.410741	0.6813
WITNESSFIRE	0.562029	0.449138	1.251352	0.2108

Mean dependent var	0.737500	S.D. dependent var	0.441374
S.E. of regression	0.430641	Akaike info criterion	1.156524
Sum squared resid	28.18868	Schwarz criterion	1.310282
Log likelihood	-84.52190	Hannan-Quinn criter.	1.218960
Restr. log likelihood	-92.10490	Avg. log likelihood	-0.528262
LR statistic (7 df)	15.16601	McFadden R-squared	0.082330
Probability(LR stat)	0.033929		

Obs with Dep=0	42	Total obs	160
Obs with Dep=1	118		

RX program with income variable for the CA whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 12:12
Sample(adjusted): 2 187
Included observations: 151
Excluded observations: 35 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.108608	1.477121	0.750520	0.4529
AGE	0.012623	0.015196	0.830703	0.4061
EDUC	-0.006314	0.092868	-0.067986	0.9458
EXPSMOKE	-0.406594	0.497923	-0.816581	0.4142
INCOME	4.97E-06	5.54E-06	0.897380	0.3695
RXBID	-0.005173	0.001444	-3.581639	0.0003
OWNHOME	-0.134231	0.558878	-0.240179	0.8102
RESPPROB	0.223579	0.534573	0.418238	0.6758
WITNESSFIRE	0.500268	0.463270	1.079861	0.2802

Mean dependent var	0.748344	S.D. dependent var	0.435409
S.E. of regression	0.422751	Akaike info criterion	1.137803
Sum squared resid	25.37799	Schwarz criterion	1.317641
Log likelihood	-76.90412	Hannan-Quinn criter.	1.210862
Restr. log likelihood	-85.18616	Avg. log likelihood	-0.509299
LR statistic (8 df)	16.56407	McFadden R-squared	0.097223
Probability(LR stat)	0.034982		

Obs with Dep=0	38	Total obs	151
Obs with Dep=1	113		

Mech program without income variable for the CA Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 12:23
Sample(adjusted): 1 187
Included observations: 178
Excluded observations: 9 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-1.834039	1.179129	-1.555418	0.1198
AGE	0.008276	0.010518	0.786852	0.4314
EDUC	0.127616	0.071541	1.783804	0.0745
EXPSMOKE	-0.872739	0.416194	-2.096954	0.0360
MECHBID	-0.001092	0.001169	-0.934424	0.3501
OWNHOME	-0.421917	0.389613	-1.082911	0.2788
RESPPROB	0.511968	0.413560	1.237952	0.2157
WITNESSFIRE	0.641898	0.400183	1.604011	0.1087

Mean dependent var	0.477528	S.D. dependent var	0.500904
S.E. of regression	0.493745	Akaike info criterion	1.407761
Sum squared resid	41.44333	Schwarz criterion	1.550762
Log likelihood	-117.2907	Hannan-Quinn criter.	1.465752
Restr. log likelihood	-123.2004	Avg. log likelihood	-0.658937
LR statistic (7 df)	11.81932	McFadden R-squared	0.047968
Probability(LR stat)	0.106659		
Obs with Dep=0	93	Total obs	178
Obs with Dep=1	85		

Mech program with income variable for the CA Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 12:23
Sample(adjusted): 1 187
Included observations: 169
Excluded observations: 18 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-1.730343	1.219913	-1.418415	0.1561
AGE	0.022553	0.012127	1.859686	0.0629
EDUC	0.076988	0.075844	1.015093	0.3101
EXPSMOKE	-1.006902	0.427771	-2.353835	0.0186
INCOME	6.36E-06	4.35E-06	1.462896	0.1435
MECHBID	-0.001431	0.001232	-1.161368	0.2455
OWNHOME	-0.653499	0.456786	-1.430647	0.1525
RESPPROB	0.482319	0.421087	1.145412	0.2520
WITNESSFIRE	0.469274	0.406473	1.154502	0.2483

Mean dependent var	0.497041	S.D. dependent var	0.501477
S.E. of regression	0.491224	Akaike info criterion	1.404132
Sum squared resid	38.60813	Schwarz criterion	1.570813
Log likelihood	-109.6492	Hannan-Quinn criter.	1.471774
Restr. log likelihood	-117.1389	Avg. log likelihood	-0.648812
LR statistic (8 df)	14.97949	McFadden R-squared	0.063939
Probability(LR stat)	0.059545		
Obs with Dep=0	85	Total obs	169
Obs with Dep=1	84		

RX program without income variable for the FL Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 12:17
Sample(adjusted): 6 328
Included observations: 269
Excluded observations: 54 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.630492	1.264420	2.080394	0.0375
AGE	-0.009558	0.009079	-1.052753	0.2925
EDUC	-0.069852	0.075253	-0.928224	0.3533
EXPSMOKE	0.217964	0.409914	0.531732	0.5949
RXBID	-0.006409	0.001370	-4.677191	0.0000
OWNHOME	0.567418	0.379563	1.494926	0.1349
RESPPROB	0.585950	0.361950	1.618870	0.1055
WITNESSFIRE	-0.224069	0.334229	-0.670406	0.5026

Mean dependent var	0.724907	S.D. dependent var	0.447393
S.E. of regression	0.429799	Akaike info criterion	1.133907
Sum squared resid	48.21381	Schwarz criterion	1.240812
Log likelihood	-144.5104	Hannan-Quinn criter.	1.176840
Restr. log likelihood	-158.2416	Avg. log likelihood	-0.537213
LR statistic (7 df)	27.46240	McFadden R-squared	0.086774
Probability(LR stat)	0.000275		
Obs with Dep=0	74	Total obs	269
Obs with Dep=1	195		

RX program with income variable for the FL whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 12:17
Sample(adjusted): 6 268
Included observations: 224
Excluded observations: 39 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.818884	1.398234	2.016032	0.0438
AGE	-0.007088	0.010296	-0.688382	0.4912
EDUC	-0.103153	0.085259	-1.209878	0.2263
EXPSMOKE	0.237063	0.474173	0.499950	0.6171
INCOME	4.36E-06	5.39E-06	0.807888	0.4192
RXBID	-0.005183	0.001536	-3.374609	0.0007
OWNHOME	0.484641	0.425458	1.139105	0.2547
RESPPROB	0.454863	0.391652	1.161395	0.2455
WITNESSFIRE	-0.365470	0.371858	-0.982821	0.3257

Mean dependent var	0.736607	S.D. dependent var	0.441460
S.E. of regression	0.432230	Akaike info criterion	1.158262
Sum squared resid	40.16681	Schwarz criterion	1.295337
Log likelihood	-120.7253	Hannan-Quinn criter.	1.213592
Restr. log likelihood	-129.1530	Avg. log likelihood	-0.538952
LR statistic (8 df)	16.85531	McFadden R-squared	0.065253
Probability(LR stat)	0.031651		
Obs with Dep=0	59	Total obs	224
Obs with Dep=1	165		

Mech program without income variable for the FL Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 12:37
Sample(adjusted): 1 328
Included observations: 305
Excluded observations: 23 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.122958	1.072151	1.047389	0.2949
AGE	-0.009726	0.007520	-1.293406	0.1959
EDUC	0.011806	0.064844	0.182060	0.8555
EXPSMOKE	-0.083175	0.350059	-0.237603	0.8122
MECHBID	-0.005247	0.001323	-3.965900	0.0001
OWNHOME	0.039233	0.324699	0.120829	0.9038
RESPPROB	0.027200	0.290499	0.093632	0.9254
WITNESSFIRE	-0.693072	0.269895	-2.567936	0.0102

Mean dependent var	0.442623	S.D. dependent var	0.497513
S.E. of regression	0.481363	Akaike info criterion	1.337167
Sum squared resid	68.81789	Schwarz criterion	1.434749
Log likelihood	-195.9179	Hannan-Quinn criter.	1.376198
Restr. log likelihood	-209.3973	Avg. log likelihood	-0.642354
LR statistic (7 df)	26.95866	McFadden R-squared	0.064372
Probability(LR stat)	0.000339		

Obs with Dep=0	170	Total obs	305
Obs with Dep=1	135		

Mech program with income variable for the FL Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 12:37
Sample(adjusted): 1 267
Included observations: 253
Excluded observations: 14 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.916944	1.194796	0.767448	0.4428
AGE	-0.006657	0.008678	-0.767028	0.4431
EDUC	-0.019276	0.073607	-0.261880	0.7934
EXPSMOKE	-0.066386	0.393322	-0.168783	0.8660
INCOME	8.44E-06	4.62E-06	1.826500	0.0678
MECHBID	-0.004047	0.001425	-2.839151	0.0045
OWNHOME	-0.022142	0.363915	-0.060843	0.9515
RESPPROB	-0.016362	0.319921	-0.051145	0.9592
WITNESSFIRE	-0.658103	0.294483	-2.234775	0.0254

Mean dependent var	0.454545	S.D. dependent var	0.498917
S.E. of regression	0.487394	Akaike info criterion	1.372019
Sum squared resid	57.96299	Schwarz criterion	1.497713
Log likelihood	-164.5604	Hannan-Quinn criter.	1.422590
Restr. log likelihood	-174.3193	Avg. log likelihood	-0.650436
LR statistic (8 df)	19.51790	McFadden R-squared	0.055983
Probability(LR stat)	0.012322		

Obs with Dep=0	138	Total obs	253
Obs with Dep=1	115		

RX program without income variable for the MT Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 12:20
Sample(adjusted): 2 270
Included observations: 215
Excluded observations: 54 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.820843	1.247751	1.459300	0.1445
AGE	-0.004866	0.010243	-0.475031	0.6348
EDUC	-0.044682	0.069718	-0.640903	0.5216
EXPSMOKE	0.343292	0.723923	0.474211	0.6353
RXBID	-0.003598	0.000969	-3.711570	0.0002
OWNHOME	-0.393659	0.423692	-0.929117	0.3528
RESPPROB	0.139544	0.364082	0.383276	0.7015
WITNESSFIRE	-0.007908	0.421549	-0.018759	0.9850

Mean dependent var	0.595349	S.D. dependent var	0.491970
S.E. of regression	0.480349	Akaike info criterion	1.343187
Sum squared resid	47.76223	Schwarz criterion	1.468606
Log likelihood	-136.3926	Hannan-Quinn criter.	1.393862
Restr. log likelihood	-145.0933	Avg. log likelihood	-0.634384
LR statistic (7 df)	17.40137	McFadden R-squared	0.059966
Probability(LR stat)	0.014984		

Obs with Dep=0	87	Total obs	215
Obs with Dep=1	128		

RX program with income variable for the MT whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 12:21
Sample(adjusted): 2 270
Included observations: 208
Excluded observations: 61 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.012367	1.278902	1.573512	0.1156
AGE	-0.008151	0.010342	-0.788199	0.4306
EDUC	-0.051089	0.075090	-0.680370	0.4963
EXPSMOKE	0.299961	0.725358	0.413535	0.6792
INCOME	4.01E-07	5.61E-06	0.071449	0.9430
RXBID	-0.003604	0.001001	-3.600902	0.0003
OWNHOME	-0.368746	0.442115	-0.834049	0.4043
RESPPROB	0.164359	0.370808	0.443246	0.6576
WITNESSFIRE	0.054202	0.426754	0.127009	0.8989

Mean dependent var	0.596154	S.D. dependent var	0.491851
S.E. of regression	0.481519	Akaike info criterion	1.353624
Sum squared resid	46.14020	Schwarz criterion	1.498037
Log likelihood	-131.7769	Hannan-Quinn criter.	1.412017
Restr. log likelihood	-140.3044	Avg. log likelihood	-0.633543
LR statistic (8 df)	17.05503	McFadden R-squared	0.060779
Probability(LR stat)	0.029541		

Obs with Dep=0	84	Total obs	208
Obs with Dep=1	124		

Mech program without income variable for the MT Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 12:40
Sample(adjusted): 1 270
Included observations: 260
Excluded observations: 10 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.577623	1.222909	0.472335	0.6367
AGE	0.003662	0.008959	0.408675	0.6828
EDUC	-0.061437	0.063795	-0.963040	0.3355
EXPSMOKE	-0.070939	0.772538	-0.091826	0.9268
MECHBID	-0.003254	0.001018	-3.195790	0.0014
OWNHOME	-0.195668	0.368624	-0.530807	0.5956
RESPPROB	0.019121	0.334417	0.057178	0.9544
WITNESSFIRE	0.177437	0.408444	0.434422	0.6640

Mean dependent var	0.334615	S.D. dependent var	0.472766
S.E. of regression	0.467377	Akaike info criterion	1.286582
Sum squared resid	55.04714	Schwarz criterion	1.396142
Log likelihood	-159.2557	Hannan-Quinn criter.	1.330626
Restr. log likelihood	-165.7238	Avg. log likelihood	-0.612522
LR statistic (7 df)	12.93620	McFadden R-squared	0.039029
Probability(LR stat)	0.073678		

Obs with Dep=0	173	Total obs	260
Obs with Dep=1	87		

Mech program with income variable for the MT Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 12:39
Sample(adjusted): 1 270
Included observations: 251
Excluded observations: 19 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.201276	1.270563	0.945467	0.3444
AGE	0.001723	0.009108	0.189171	0.8500
EDUC	-0.111131	0.069934	-1.589089	0.1120
EXPSMOKE	-0.052889	0.772875	-0.068432	0.9454
INCOME	4.43E-06	4.95E-06	0.896400	0.3700
MECHBID	-0.003192	0.001047	-3.049698	0.0023
OWNHOME	-0.218402	0.385155	-0.567051	0.5707
RESPPROB	0.031506	0.338581	0.093052	0.9259
WITNESSFIRE	0.146003	0.412935	0.353573	0.7237

Mean dependent var	0.338645	S.D. dependent var	0.474195
S.E. of regression	0.469559	Akaike info criterion	1.298922
Sum squared resid	53.35755	Schwarz criterion	1.425333
Log likelihood	-154.0148	Hannan-Quinn criter.	1.349793
Restr. log likelihood	-160.6734	Avg. log likelihood	-0.613605
LR statistic (8 df)	13.31719	McFadden R-squared	0.041442
Probability(LR stat)	0.101392		

Obs with Dep=0	166	Total obs	251
Obs with Dep=1	85		

RX program without income variable for the CA Hispanics

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 12:14
Sample(adjusted): 1 306
Included observations: 269
Excluded observations: 37 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	4.179496	1.145838	3.647546	0.0003
AGE	-0.015961	0.012180	-1.310423	0.1901
EDUC	-0.127011	0.074397	-1.707211	0.0878
EXPSMOKE	0.808730	0.445765	1.814252	0.0696
RXBID	-0.001972	0.001111	-1.774114	0.0760
OWNHOME	-0.457249	0.346699	-1.318867	0.1872
RESPPROB	-0.641899	0.449504	-1.428016	0.1533
WITNESSFIRE	-0.181172	0.479902	-0.377519	0.7058

Mean dependent var	0.828996	S.D. dependent var	0.377214
S.E. of regression	0.371788	Akaike info criterion	0.918730
Sum squared resid	36.07708	Schwarz criterion	1.025636
Log likelihood	-115.5692	Hannan-Quinn criter.	0.961664
Restr. log likelihood	-123.0606	Avg. log likelihood	-0.429625
LR statistic (7 df)	14.98276	McFadden R-squared	0.060876
Probability(LR stat)	0.036221		
Obs with Dep=0	46	Total obs	269
Obs with Dep=1	223		

RX program with income variable for the CA Hispanics

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 12:14
Sample(adjusted): 1 306
Included observations: 256
Excluded observations: 50 after adjusting endpoints
Convergence achieved after 6 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.825226	1.196364	3.197376	0.0014
AGE	-0.009773	0.013448	-0.726768	0.4674
EDUC	-0.103113	0.082692	-1.246951	0.2124
EXPSMOKE	0.761828	0.466739	1.632235	0.1026
INCOME	-6.87E-06	6.83E-06	-1.005119	0.3148
RXBID	-0.001927	0.001156	-1.667866	0.0953
OWNHOME	-0.284780	0.369681	-0.770339	0.4411
RESPPROB	-0.733312	0.454880	-1.612102	0.1069
WITNESSFIRE	-0.114938	0.510913	-0.224965	0.8220

Mean dependent var	0.832031	S.D. dependent var	0.374571
S.E. of regression	0.367702	Akaike info criterion	0.916496
Sum squared resid	33.39561	Schwarz criterion	1.041131
Log likelihood	-108.3114	Hannan-Quinn criter.	0.966623
Restr. log likelihood	-115.8786	Avg. log likelihood	-0.423092
LR statistic (8 df)	15.13432	McFadden R-squared	0.065302
Probability(LR stat)	0.056586		
Obs with Dep=0	43	Total obs	256
Obs with Dep=1	213		

Mech program without income variable for the CA Hispanics

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 12:24
Sample(adjusted): 1 306
Included observations: 291
Excluded observations: 15 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.705136	0.906095	2.985488	0.0028
AGE	0.009856	0.010120	0.973882	0.3301
EDUC	-0.186685	0.061455	-3.037770	0.0024
EXPSMOKE	0.233034	0.330285	0.705554	0.4805
MECHBID	-0.000255	0.000876	-0.291177	0.7709
OWNHOME	-0.189796	0.271583	-0.698851	0.4846
RESPPROB	-0.577955	0.360195	-1.604559	0.1086
WITNESSFIRE	0.404578	0.374483	1.080364	0.2800

Mean dependent var	0.680412	S.D. dependent var	0.467120
S.E. of regression	0.457564	Akaike info criterion	1.240737
Sum squared resid	59.25022	Schwarz criterion	1.341722
Log likelihood	-172.5272	Hannan-Quinn criter.	1.281192
Restr. log likelihood	-182.3284	Avg. log likelihood	-0.592877
LR statistic (7 df)	19.60241	McFadden R-squared	0.053756
Probability(LR stat)	0.006496		

Obs with Dep=0	93	Total obs	291
Obs with Dep=1	198		

Mech program with income variable for the CA Hispanics

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 12:24
Sample(adjusted): 1 306
Included observations: 278
Excluded observations: 28 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.571852	0.943162	2.726841	0.0064
AGE	0.012704	0.010849	1.170976	0.2416
EDUC	-0.182581	0.067036	-2.723614	0.0065
EXPSMOKE	0.223633	0.339095	0.659500	0.5096
INCOME	1.27E-06	5.64E-06	0.224712	0.8222
MECHBID	-0.000474	0.000896	-0.528520	0.5971
OWNHOME	-0.207635	0.293699	-0.706964	0.4796
RESPPROB	-0.664235	0.365461	-1.817524	0.0691
WITNESSFIRE	0.409635	0.387726	1.056506	0.2907

Mean dependent var	0.679856	S.D. dependent var	0.467373
S.E. of regression	0.458279	Akaike info criterion	1.248409
Sum squared resid	56.49520	Schwarz criterion	1.365850
Log likelihood	-164.5288	Hannan-Quinn criter.	1.295525
Restr. log likelihood	-174.2998	Avg. log likelihood	-0.591830
LR statistic (8 df)	19.54203	McFadden R-squared	0.056059
Probability(LR stat)	0.012215		

Obs with Dep=0	89	Total obs	278
Obs with Dep=1	189		

RX program without income variable for the FL Hispanics

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 12:19
Sample(adjusted): 3 340
Included observations: 265
Excluded observations: 73 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.833614	1.239539	2.286022	0.0223
AGE	-0.004591	0.008850	-0.518750	0.6039
EDUC	-0.096943	0.081114	-1.195144	0.2320
EXPSMOKE	0.156956	0.316764	0.495497	0.6202
RXBID	-0.003793	0.001205	-3.147246	0.0016
OWNHOME	-0.325824	0.339214	-0.960524	0.3368
RESPPROB	0.306102	0.349576	0.875638	0.3812
WITNESSFIRE	0.067705	0.310553	0.218014	0.8274

Mean dependent var	0.667925	S.D. dependent var	0.471849
S.E. of regression	0.465519	Akaike info criterion	1.280544
Sum squared resid	55.69405	Schwarz criterion	1.388611
Log likelihood	-161.6721	Hannan-Quinn criter.	1.323964
Restr. log likelihood	-168.4443	Avg. log likelihood	-0.610083
LR statistic (7 df)	13.54434	McFadden R-squared	0.040204
Probability(LR stat)	0.059905		
Obs with Dep=0	88	Total obs	265
Obs with Dep=1	177		

RX program with income variable for the FL Hispanics

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 12:18
Sample(adjusted): 3 280
Included observations: 222
Excluded observations: 56 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.154681	1.306554	1.649133	0.0991
AGE	-0.007030	0.009781	-0.718706	0.4723
EDUC	-0.054066	0.086901	-0.622150	0.5338
EXPSMOKE	-0.006315	0.336081	-0.018790	0.9850
INCOME	-1.38E-06	6.43E-06	-0.215093	0.8297
RXBID	-0.003737	0.001283	-2.911403	0.0036
OWNHOME	-0.197069	0.368869	-0.534254	0.5932
RESPPROB	0.307243	0.371034	0.828072	0.4076
WITNESSFIRE	0.270537	0.330719	0.818029	0.4133

Mean dependent var	0.639640	S.D. dependent var	0.481190
S.E. of regression	0.477380	Akaike info criterion	1.337318
Sum squared resid	48.54101	Schwarz criterion	1.475264
Log likelihood	-139.4423	Hannan-Quinn criter.	1.393012
Restr. log likelihood	-145.1048	Avg. log likelihood	-0.628118
LR statistic (8 df)	11.32508	McFadden R-squared	0.039024
Probability(LR stat)	0.183951		
Obs with Dep=0	80	Total obs	222
Obs with Dep=1	142		

Mech program without income variable for the FL Hispanics

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 12:38
Sample(adjusted): 2 342
Included observations: 286
Excluded observations: 55 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.445130	1.171981	2.939579	0.0033
AGE	-0.006142	0.007996	-0.768152	0.4424
EDUC	-0.211594	0.076370	-2.770635	0.0056
EXPSMOKE	0.148049	0.277799	0.532936	0.5941
MECHBID	-0.002164	0.001079	-2.004659	0.0450
OWNHOME	0.103761	0.297631	0.348622	0.7274
RESPPROB	0.207939	0.305795	0.679995	0.4965
WITNESSFIRE	-0.201017	0.272668	-0.737221	0.4610

Mean dependent var	0.496503	S.D. dependent var	0.500864
S.E. of regression	0.495766	Akaike info criterion	1.398370
Sum squared resid	68.32805	Schwarz criterion	1.500635
Log likelihood	-191.9669	Hannan-Quinn criter.	1.439361
Restr. log likelihood	-198.2331	Avg. log likelihood	-0.671213
LR statistic (7 df)	12.53243	McFadden R-squared	0.031610
Probability(LR stat)	0.084354		
Obs with Dep=0	144	Total obs	286
Obs with Dep=1	142		

Mech program with income variable for the FL Hispanics

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 12:38
Sample(adjusted): 2 280
Included observations: 238
Excluded observations: 41 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.948093	1.266138	2.328414	0.0199
AGE	-0.011809	0.009056	-1.304041	0.1922
EDUC	-0.153663	0.083152	-1.847980	0.0646
EXPSMOKE	-0.071523	0.298682	-0.239463	0.8107
INCOME	-5.57E-07	6.01E-06	-0.092609	0.9262
MECHBID	-0.002328	0.001184	-1.966050	0.0493
OWNHOME	0.033866	0.334175	0.101343	0.9193
RESPPROB	0.156186	0.333409	0.468450	0.6395
WITNESSFIRE	-0.083435	0.294134	-0.283663	0.7767

Mean dependent var	0.466387	S.D. dependent var	0.499920
S.E. of regression	0.498508	Akaike info criterion	1.419029
Sum squared resid	56.90878	Schwarz criterion	1.550333
Log likelihood	-159.8644	Hannan-Quinn criter.	1.471947
Restr. log likelihood	-164.4308	Avg. log likelihood	-0.671699
LR statistic (8 df)	9.132795	McFadden R-squared	0.027771
Probability(LR stat)	0.331218		
Obs with Dep=0	127	Total obs	238
Obs with Dep=1	111		

APPENDIX 4: **Three state pooled data regressions for 2 programs without state variables** (Protest responses included)

RX program without income variable for the Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/08/04 Time: 23:49
Sample(adjusted): 6 785
Included observations: 644
Excluded observations: 136 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.706750	0.714862	2.387525	0.0170
AGE	-0.003828	0.005805	-0.659411	0.5096
EDUC	-0.004354	0.042719	-0.101932	0.9188
EXPSMOKE	-0.072244	0.264731	-0.272898	0.7849
OWNHOME	0.025506	0.236698	0.107759	0.9142
RESPPROB	0.279446	0.222156	1.257881	0.2084
RXBID	-0.004599	0.000661	-6.959740	0.0000
WITNESSFIRE	-0.038509	0.217407	-0.177128	0.8594

Mean dependent var	0.684783	S.D. dependent var	0.464964
S.E. of regression	0.448429	Akaike info criterion	1.189022
Sum squared resid	127.8924	Schwarz criterion	1.244521
Log likelihood	-374.8651	Hannan-Quinn criter.	1.210558
Restr. log likelihood	-401.3484	Avg. log likelihood	-0.582089
LR statistic (7 df)	52.96665	McFadden R-squared	0.065986
Probability(LR stat)	3.76E-09		
Obs with Dep=0	203	Total obs	644
Obs with Dep=1	441		

RX program with income variable for the Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/08/04 Time: 23:48
Sample(adjusted): 6 707
Included observations: 583
Excluded observations: 119 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.021789	0.759003	2.663744	0.0077
AGE	-0.001395	0.006329	-0.220391	0.8256
EDUC	-0.040579	0.047045	-0.862560	0.3884
EXPSMOKE	-0.116978	0.291075	-0.401882	0.6878
INCOME	4.68E-06	2.96E-06	1.582250	0.1136
OWNHOME	-0.080822	0.259265	-0.311736	0.7552
RESPPROB	0.263233	0.233286	1.128373	0.2592
RXBID	-0.004462	0.000699	-6.380257	0.0000
WITNESSFIRE	-0.093498	0.230577	-0.405493	0.6851

Mean dependent var	0.689537	S.D. dependent var	0.463081
S.E. of regression	0.447596	Akaike info criterion	1.188966
Sum squared resid	114.9967	Schwarz criterion	1.256399
Log likelihood	-337.5835	Hannan-Quinn criter.	1.215250
Restr. log likelihood	-361.1514	Avg. log likelihood	-0.579045
LR statistic (8 df)	47.13593	McFadden R-squared	0.065258
Probability(LR stat)	1.44E-07		
Obs with Dep=0	181	Total obs	583
Obs with Dep=1	402		

Mech program without income variable for the Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/08/04 Time: 23:45
Sample(adjusted): 1 787
Included observations: 743
Excluded observations: 44 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.141931	0.618515	0.229471	0.8185
AGE	-0.000182	0.004918	-0.036929	0.9705
EDUC	0.035368	0.036732	0.962849	0.3356
EXPSMOKE	-0.371279	0.231123	-1.606412	0.1082
OWNHOME	-0.171358	0.198847	-0.861760	0.3888
RESPPROB	0.104484	0.187709	0.556626	0.5778
MECHBID	-0.003222	0.000637	-5.057949	0.0000
WITNESSFIRE	-0.193687	0.185205	-1.045795	0.2957

Mean dependent var	0.413190	S.D. dependent var	0.492738
S.E. of regression	0.482861	Akaike info criterion	1.329692
Sum squared resid	171.3686	Schwarz criterion	1.379336
Log likelihood	-485.9807	Hannan-Quinn criter.	1.348830
Restr. log likelihood	-503.7529	Avg. log likelihood	-0.654079
LR statistic (7 df)	35.54442	McFadden R-squared	0.035280
Probability(LR stat)	8.83E-06		
Obs with Dep=0	436	Total obs	743
Obs with Dep=1	307		

Mech program with income variable for the Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/08/04 Time: 23:44
Sample(adjusted): 1 707
Included observations: 673
Excluded observations: 34 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.345770	0.657867	0.525593	0.5992
AGE	0.004723	0.005381	0.877819	0.3800
EDUC	-0.008122	0.040408	-0.200999	0.8407
EXPSMOKE	-0.449564	0.249215	-1.803919	0.0712
INCOME	6.47E-06	2.44E-06	2.649082	0.0081
OWNHOME	-0.280041	0.217327	-1.288571	0.1975
RESPPROB	0.110010	0.197590	0.556760	0.5777
MECHBID	-0.003001	0.000668	-4.494246	0.0000
WITNESSFIRE	-0.205912	0.196376	-1.048559	0.2944

Mean dependent var	0.421991	S.D. dependent var	0.494244
S.E. of regression	0.483095	Akaike info criterion	1.332534
Sum squared resid	154.9652	Schwarz criterion	1.392870
Log likelihood	-439.3978	Hannan-Quinn criter.	1.355900
Restr. log likelihood	-458.2636	Avg. log likelihood	-0.652894
LR statistic (8 df)	37.73157	McFadden R-squared	0.041168
Probability(LR stat)	8.44E-06		
Obs with Dep=0	389	Total obs	673
Obs with Dep=1	284		

RX program without income variable for the Hispanics

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/08/04 Time: 23:51
Sample(adjusted): 1 648
Included observations: 534
Excluded observations: 114 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	4.361548	0.734454	5.938490	0.0000
AGE	-0.010156	0.006947	-1.461911	0.1438
EDUC	-0.170129	0.048728	-3.491394	0.0005
EXPSMOKE	0.292544	0.249152	1.174157	0.2403
OWNHOME	-0.510515	0.235237	-2.170211	0.0300
RESPPROB	-0.056335	0.275935	-0.204160	0.8382
RXBID	-0.002509	0.000785	-3.196870	0.0014
WITNESSFIRE	-0.008625	0.257254	-0.033529	0.9733

Mean dependent var	0.749064	S.D. dependent var	0.433958
S.E. of regression	0.424176	Akaike info criterion	1.094521
Sum squared resid	94.64071	Schwarz criterion	1.158646
Log likelihood	-284.2370	Hannan-Quinn criter.	1.119612
Restr. log likelihood	-300.8350	Avg. log likelihood	-0.532279
LR statistic (7 df)	33.19605	McFadden R-squared	0.055173
Probability(LR stat)	2.43E-05		
Obs with Dep=0	134	Total obs	534
Obs with Dep=1	400		

RX program with income variable for the Hispanics

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/08/04 Time: 23:51
Sample(adjusted): 1 588
Included observations: 478
Excluded observations: 110 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	4.333763	0.760865	5.695838	0.0000
AGE	-0.010212	0.007543	-1.353883	0.1758
EDUC	-0.169246	0.052222	-3.240871	0.0012
EXPSMOKE	0.174908	0.259917	0.672936	0.5010
INCOME	-1.83E-06	4.55E-06	-0.402199	0.6875
OWNHOME	-0.425171	0.249263	-1.705708	0.0881
RESPPROB	-0.111326	0.287246	-0.387564	0.6983
RXBID	-0.002429	0.000816	-2.977438	0.0029
WITNESSFIRE	0.109932	0.271616	0.404734	0.6857

Mean dependent var	0.742678	S.D. dependent var	0.437616
S.E. of regression	0.428225	Akaike info criterion	1.114380
Sum squared resid	86.00383	Schwarz criterion	1.192887
Log likelihood	-257.3368	Hannan-Quinn criter.	1.145245
Restr. log likelihood	-272.5734	Avg. log likelihood	-0.538361
LR statistic (8 df)	30.47331	McFadden R-squared	0.055899
Probability(LR stat)	0.000174		
Obs with Dep=0	123	Total obs	478
Obs with Dep=1	355		

Mech program without income variable for the Hispanics

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/08/04 Time: 23:46
Sample(adjusted): 1 650
Included observations: 577
Excluded observations: 73 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.742958	0.631399	5.928042	0.0000
AGE	-0.001079	0.006024	-0.179180	0.8578
EDUC	-0.240011	0.043387	-5.531849	0.0000
EXPSMOKE	0.166380	0.208661	0.797366	0.4252
OWNHOME	-0.119737	0.193017	-0.620345	0.5350
RESPPROB	-0.145526	0.233344	-0.623651	0.5329
MECHBID	-0.000901	0.000663	-1.358982	0.1742
WITNESSFIRE	0.012428	0.215506	0.057668	0.9540

Mean dependent var	0.589255	S.D. dependent var	0.492396
S.E. of regression	0.479544	Akaike info criterion	1.315260
Sum squared resid	130.8486	Schwarz criterion	1.375681
Log likelihood	-371.4525	Hannan-Quinn criter.	1.338821
Restr. log likelihood	-390.7032	Avg. log likelihood	-0.643765
LR statistic (7 df)	38.50147	McFadden R-squared	0.049272
Probability(LR stat)	2.43E-06		

Obs with Dep=0	237	Total obs	577
Obs with Dep=1	340		

Mech program with income variable for the Hispanics

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/08/04 Time: 23:47
Sample(adjusted): 1 588
Included observations: 516
Excluded observations: 72 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.695371	0.657166	5.623188	0.0000
AGE	-0.002638	0.006544	-0.403157	0.6868
EDUC	-0.231412	0.046406	-4.986675	0.0000
EXPSMOKE	0.044517	0.218301	0.203924	0.8384
INCOME	2.85E-06	3.91E-06	0.729475	0.4657
OWNHOME	-0.224847	0.209091	-1.075353	0.2822
RESPPROB	-0.242678	0.246702	-0.983688	0.3253
MECHBID	-0.001082	0.000693	-1.560464	0.1187
WITNESSFIRE	0.080951	0.227552	0.355748	0.7220

Mean dependent var	0.581395	S.D. dependent var	0.493809
S.E. of regression	0.481223	Akaike info criterion	1.325811
Sum squared resid	117.4088	Schwarz criterion	1.399871
Log likelihood	-333.0593	Hannan-Quinn criter.	1.354833
Restr. log likelihood	-350.7962	Avg. log likelihood	-0.645464
LR statistic (8 df)	35.47382	McFadden R-squared	0.050562
Probability(LR stat)	2.19E-05		

Obs with Dep=0	216	Total obs	516
Obs with Dep=1	300		

APPEDIX 5: **Two state pooled data regression for two programs without state variable** (Protest responses included)

RX program without income variable for the CA-FL Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 12:00
Sample(adjusted): 2 515
Included observations: 429
Excluded observations: 85 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.791637	0.922748	1.941633	0.0522
AGE	-0.005821	0.007273	-0.800262	0.4236
EDUC	-0.011127	0.055854	-0.199222	0.8421
EXPSMOKE	-0.034626	0.297417	-0.116424	0.9073
RXBID	-0.005228	0.000932	-5.608848	0.0000
OWNHOME	0.330810	0.292489	1.131019	0.2580
RESPPROB	0.393618	0.291137	1.352000	0.1764
WITNESSFIRE	0.098377	0.262660	0.374541	0.7080

Mean dependent var	0.729604	S.D. dependent var	0.444683
S.E. of regression	0.430406	Akaike info criterion	1.122472
Sum squared resid	77.99006	Schwarz criterion	1.198210
Log likelihood	-232.7701	Hannan-Quinn criter.	1.152381
Restr. log likelihood	-250.3870	Avg. log likelihood	-0.542588
LR statistic (7 df)	35.23362	McFadden R-squared	0.070358
Probability(LR stat)	1.01E-05		

Obs with Dep=0	116	Total obs	429
Obs with Dep=1	313		

RX program with income variable for the CA-FL Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 12:00
Sample(adjusted): 2 455
Included observations: 375
Excluded observations: 79 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.031040	0.998120	2.034865	0.0419
AGE	5.14E-05	0.008303	0.006185	0.9951
EDUC	-0.052017	0.062259	-0.835499	0.4034
EXPSMOKE	-0.075156	0.332442	-0.226071	0.8211
INCOME	4.73E-06	3.67E-06	1.291635	0.1965
RXBID	-0.004983	0.001010	-4.934233	0.0000
OWNHOME	0.204168	0.329189	0.620216	0.5351
RESPPROB	0.356675	0.312418	1.141660	0.2536
WITNESSFIRE	0.007349	0.283939	0.025883	0.9794

Mean dependent var	0.741333	S.D. dependent var	0.438487
S.E. of regression	0.427401	Akaike info criterion	1.117139
Sum squared resid	66.85777	Schwarz criterion	1.211385
Log likelihood	-200.4636	Hannan-Quinn criter.	1.154555
Restr. log likelihood	-214.3716	Avg. log likelihood	-0.534570
LR statistic (8 df)	27.81611	McFadden R-squared	0.064878
Probability(LR stat)	0.000511		

Obs with Dep=0	97	Total obs	375
Obs with Dep=1	278		

Mech program without income variable for the CA-FL Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 11:51
Sample(adjusted): 1 515
Included observations: 483
Excluded observations: 32 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.198433	0.763757	-0.259812	0.7950
AGE	-0.003412	0.005942	-0.574204	0.5658
EDUC	0.069963	0.046727	1.497278	0.1343
EXPSMOKE	-0.313616	0.250227	-1.253324	0.2101
MECHBID	-0.002948	0.000838	-3.517360	0.0004
OWNHOME	-0.136519	0.240111	-0.568567	0.5696
RESPPROB	0.136291	0.230097	0.592322	0.5536
WITNESSFIRE	-0.236744	0.214413	-1.104149	0.2695

Mean dependent var	0.455487	S.D. dependent var	0.498531
S.E. of regression	0.491581	Akaike info criterion	1.370071
Sum squared resid	114.7845	Schwarz criterion	1.439305
Log likelihood	-322.8722	Hannan-Quinn criter.	1.397278
Restr. log likelihood	-332.8735	Avg. log likelihood	-0.668472
LR statistic (7 df)	20.00262	McFadden R-squared	0.030045
Probability(LR stat)	0.005564		
Obs with Dep=0	263	Total obs	483
Obs with Dep=1	220		

Mech program with income variable for the CA-FL Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 11:53
Sample(adjusted): 1 454
Included observations: 422
Excluded observations: 32 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.315602	0.820297	-0.384741	0.7004
AGE	0.004627	0.006787	0.681709	0.4954
EDUC	0.037911	0.051434	0.737089	0.4611
EXPSMOKE	-0.405870	0.272747	-1.488083	0.1367
INCOME	6.42E-06	2.91E-06	2.201227	0.0277
MECHBID	-0.002575	0.000893	-2.881470	0.0040
OWNHOME	-0.273629	0.269883	-1.013880	0.3106
RESPPROB	0.147490	0.247528	0.595851	0.5513
WITNESSFIRE	-0.240705	0.230539	-1.044097	0.2964

Mean dependent var	0.471564	S.D. dependent var	0.499783
S.E. of regression	0.492382	Akaike info criterion	1.377417
Sum squared resid	100.1275	Schwarz criterion	1.463685
Log likelihood	-281.6351	Hannan-Quinn criter.	1.411508
Restr. log likelihood	-291.8253	Avg. log likelihood	-0.667382
LR statistic (8 df)	20.38039	McFadden R-squared	0.034919
Probability(LR stat)	0.008989		
Obs with Dep=0	223	Total obs	422
Obs with Dep=1	199		

RX program without income variable for the CA-MT Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 12:01
Sample(adjusted): 2 457
Included observations: 375
Excluded observations: 81 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.329323	0.870475	1.527125	0.1267
AGE	0.000228	0.007772	0.029379	0.9766
EDUC	0.022012	0.052090	0.422577	0.6726
EXPSMOKE	-0.299384	0.357291	-0.837928	0.4021
RXBID	-0.003976	0.000770	-5.165551	0.0000
OWNHOME	-0.296280	0.306758	-0.965842	0.3341
RESPPROB	0.110575	0.289000	0.382612	0.7020
WITNESSFIRE	0.137145	0.300128	0.456953	0.6477

Mean dependent var	0.656000	S.D. dependent var	0.475676
S.E. of regression	0.461150	Akaike info criterion	1.249616
Sum squared resid	78.04597	Schwarz criterion	1.333391
Log likelihood	-226.3031	Hannan-Quinn criter.	1.282875
Restr. log likelihood	-241.3699	Avg. log likelihood	-0.603475
LR statistic (7 df)	30.13366	McFadden R-squared	0.062422
Probability(LR stat)	8.97E-05		
Obs with Dep=0	129	Total obs	375
Obs with Dep=1	246		

RX program with income variable for the CA-MT Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 12:02
Sample(adjusted): 2 457
Included observations: 359
Excluded observations: 97 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.719141	0.907532	1.894305	0.0582
AGE	0.001683	0.008204	0.205159	0.8374
EDUC	-0.019583	0.056734	-0.345180	0.7300
EXPSMOKE	-0.333375	0.378369	-0.881085	0.3783
INCOME	5.29E-06	3.56E-06	1.484715	0.1376
RXBID	-0.004116	0.000804	-5.120149	0.0000
OWNHOME	-0.420480	0.331082	-1.270020	0.2041
RESPPROB	0.157704	0.295541	0.533612	0.5936
WITNESSFIRE	0.140439	0.307557	0.456626	0.6479

Mean dependent var	0.660167	S.D. dependent var	0.474313
S.E. of regression	0.458014	Akaike info criterion	1.241283
Sum squared resid	73.42177	Schwarz criterion	1.338637
Log likelihood	-213.8103	Hannan-Quinn criter.	1.279997
Restr. log likelihood	-230.0919	Avg. log likelihood	-0.595572
LR statistic (8 df)	32.56321	McFadden R-squared	0.070761
Probability(LR stat)	7.38E-05		
Obs with Dep=0	122	Total obs	359
Obs with Dep=1	237		

Mech program without income variable for the CA-MT Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 11:51
Sample(adjusted): 1 515
Included observations: 483
Excluded observations: 32 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.198433	0.763757	-0.259812	0.7950
AGE	-0.003412	0.005942	-0.574204	0.5658
EDUC	0.069963	0.046727	1.497278	0.1343
EXPSMOKE	-0.313616	0.250227	-1.253324	0.2101
MECHBID	-0.002948	0.000838	-3.517360	0.0004
OWNHOME	-0.136519	0.240111	-0.568567	0.5696
RESPPROB	0.136291	0.230097	0.592322	0.5536
WITNESSFIRE	-0.236744	0.214413	-1.104149	0.2695

Mean dependent var	0.455487	S.D. dependent var	0.498531
S.E. of regression	0.491581	Akaike info criterion	1.370071
Sum squared resid	114.7845	Schwarz criterion	1.439305
Log likelihood	-322.8722	Hannan-Quinn criter.	1.397278
Restr. log likelihood	-332.8735	Avg. log likelihood	-0.668472
LR statistic (7 df)	20.00262	McFadden R-squared	0.030045
Probability(LR stat)	0.005564		

Obs with Dep=0	263	Total obs	483
Obs with Dep=1	220		

Mech program with income variable for the CA-MT Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 11:53
Sample(adjusted): 1 454
Included observations: 422
Excluded observations: 32 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.315602	0.820297	-0.384741	0.7004
AGE	0.004627	0.006787	0.681709	0.4954
EDUC	0.037911	0.051434	0.737089	0.4611
EXPSMOKE	-0.405870	0.272747	-1.488083	0.1367
INCOME	6.42E-06	2.91E-06	2.201227	0.0277
MECHBID	-0.002575	0.000893	-2.881470	0.0040
OWNHOME	-0.273629	0.269883	-1.013880	0.3106
RESPPROB	0.147490	0.247528	0.595851	0.5513
WITNESSFIRE	-0.240705	0.230539	-1.044097	0.2964

Mean dependent var	0.471564	S.D. dependent var	0.499783
S.E. of regression	0.492382	Akaike info criterion	1.377417
Sum squared resid	100.1275	Schwarz criterion	1.463685
Log likelihood	-281.6351	Hannan-Quinn criter.	1.411508
Restr. log likelihood	-291.8253	Avg. log likelihood	-0.667382
LR statistic (8 df)	20.38039	McFadden R-squared	0.034919
Probability(LR stat)	0.008989		

Obs with Dep=0	223	Total obs	422
Obs with Dep=1	199		

RX program without income variable for the FL-MT Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 12:04
Sample(adjusted): 6 598
Included observations: 484
Excluded observations: 109 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.107375	0.857117	2.458678	0.0139
AGE	-0.005836	0.006625	-0.880954	0.3783
EDU	-0.038198	0.050257	-0.760041	0.4472
EXPSMOKE	0.151414	0.341069	0.443938	0.6571
RXBID	-0.004752	0.000776	-6.125089	0.0000
OWNHOME	0.077590	0.278354	0.278744	0.7804
RESPPROB	0.339266	0.249480	1.359896	0.1739
WITNESSFIRE	-0.241469	0.252834	-0.955049	0.3396

Mean dependent var	0.667355	S.D. dependent var	0.471648
S.E. of regression	0.453496	Akaike info criterion	1.213952
Sum squared resid	97.89351	Schwarz criterion	1.283077
Log likelihood	-285.7763	Hannan-Quinn criter.	1.241114
Restr. log likelihood	-307.8413	Avg. log likelihood	-0.590447
LR statistic (7 df)	44.12990	McFadden R-squared	0.071676
Probability(LR stat)	2.02E-07		
Obs with Dep=0	161	Total obs	484
Obs with Dep=1	323		

RX program with income variable for the FL-MT Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 12:03
Sample(adjusted): 6 598
Included observations: 432
Excluded observations: 161 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.387192	0.912592	2.615838	0.0089
AGE	-0.006086	0.007130	-0.853514	0.3934
EDU	-0.061510	0.055462	-1.109061	0.2674
EXPSMOKE	0.106911	0.378443	0.282502	0.7776
INCOME	3.00E-06	3.80E-06	0.790526	0.4292
RXBID	-0.004383	0.000819	-5.350808	0.0000
OWNHOME	0.035300	0.302531	0.116683	0.9071
RESPPROB	0.286019	0.262677	1.088864	0.2762
WITNESSFIRE	-0.302802	0.270786	-1.118234	0.2635

Mean dependent var	0.668981	S.D. dependent var	0.471125
S.E. of regression	0.456212	Akaike info criterion	1.229712
Sum squared resid	88.03872	Schwarz criterion	1.314471
Log likelihood	-256.6178	Hannan-Quinn criter.	1.263174
Restr. log likelihood	-274.2758	Avg. log likelihood	-0.594023
LR statistic (8 df)	35.31600	McFadden R-squared	0.064380
Probability(LR stat)	2.34E-05		
Obs with Dep=0	143	Total obs	432
Obs with Dep=1	289		

Mech program without income variable for the FL-MT Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 11:58
Sample(adjusted): 1 598
Included observations: 565
Excluded observations: 33 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.932114	0.761150	1.224614	0.2207
AGE	-0.002639	0.005681	-0.464469	0.6423
EDU	-0.012896	0.044240	-0.291507	0.7707
EXPSMOKE	-0.153752	0.305916	-0.502596	0.6152
MECHBID	-0.004168	0.000796	-5.234607	0.0000
OWNHOME	-0.060750	0.240593	-0.252502	0.8007
RESPPROB	0.009107	0.216646	0.042037	0.9665
WITNESSFIRE	-0.453752	0.213090	-2.129392	0.0332

Mean dependent var	0.392920	S.D. dependent var	0.488832
S.E. of regression	0.474564	Akaike info criterion	1.299827
Sum squared resid	125.4426	Schwarz criterion	1.361233
Log likelihood	-359.2011	Hannan-Quinn criter.	1.323795
Restr. log likelihood	-378.5706	Avg. log likelihood	-0.635754
LR statistic (7 df)	38.73913	McFadden R-squared	0.051165
Probability(LR stat)	2.19E-06		

Obs with Dep=0	343	Total obs	565
Obs with Dep=1	222		

Mech program with income variable for the FL-MT

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 11:58
Sample(adjusted): 1 598
Included observations: 504
Excluded observations: 94 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.211696	0.822916	1.472442	0.1409
AGE	-0.001232	0.006188	-0.199072	0.8422
EDU	-0.058596	0.049432	-1.185387	0.2359
EXPSMOKE	-0.175992	0.334925	-0.525466	0.5993
INCOME	6.87E-06	3.31E-06	2.077603	0.0377
MECHBID	-0.003701	0.000829	-4.465567	0.0000
OWNHOME	-0.127059	0.261449	-0.485981	0.6270
RESPPROB	-0.001042	0.230041	-0.004528	0.9964
WITNESSFIRE	-0.439819	0.228328	-1.926263	0.0541

Mean dependent var	0.396825	S.D. dependent var	0.489725
S.E. of regression	0.477004	Akaike info criterion	1.313184
Sum squared resid	112.6287	Schwarz criterion	1.388587
Log likelihood	-321.9223	Hannan-Quinn criter.	1.342762
Restr. log likelihood	-338.5385	Avg. log likelihood	-0.638735
LR statistic (8 df)	33.23246	McFadden R-squared	0.049082
Probability(LR stat)	5.59E-05		

Obs with Dep=0	304	Total obs	504
Obs with Dep=1	200		

APPENDIX 6: **Regressions on significant independent variables (Reduced form)** (Protest responses included)

RX program for the CA Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 23:04
Sample(adjusted): 2 187
Included observations: 162
Excluded observations: 24 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.813490	0.301713	6.010637	0.0000
RXBID	-0.004611	0.001315	-3.507788	0.0005

Mean dependent var	0.740741	S.D. dependent var	0.439587
S.E. of regression	0.423486	Akaike info criterion	1.090225
Sum squared resid	28.69445	Schwarz criterion	1.128343
Log likelihood	-86.30820	Hannan-Quinn criter.	1.105701
Restr. log likelihood	-92.70947	Avg. log likelihood	-0.532767
LR statistic (1 df)	12.80254	McFadden R-squared	0.069047
Probability(LR stat)	0.000346		
Obs with Dep=0	42	Total obs	162
Obs with Dep=1	120		

Mech program for the CA Whites

RX program for the FL Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 23:10
Sample(adjusted): 6 328
Included observations: 277
Excluded observations: 46 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.632138	0.213982	7.627468	0.0000
RXBID	-0.005938	0.001303	-4.558692	0.0000

Mean dependent var	0.718412	S.D. dependent var	0.450588
S.E. of regression	0.433251	Akaike info criterion	1.125273
Sum squared resid	51.61926	Schwarz criterion	1.151439
Log likelihood	-153.8503	Hannan-Quinn criter.	1.135772
Restr. log likelihood	-164.6619	Avg. log likelihood	-0.555416
LR statistic (1 df)	21.62313	McFadden R-squared	0.065659
Probability(LR stat)	3.32E-06		
Obs with Dep=0	78	Total obs	277
Obs with Dep=1	199		

Mech program for the FL Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 23:18
Sample(adjusted): 1 267
Included observations: 260
Excluded observations: 7 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.237248	0.335949	0.706202	0.4801
MECHBID	-0.003944	0.001402	-2.814101	0.0049
INCOME	8.42E-06	4.16E-06	2.025419	0.0428
WITNESSFIRE	-0.689370	0.268295	-2.569453	0.0102

Mean dependent var	0.453846	S.D. dependent var	0.498825
S.E. of regression	0.483258	Akaike info criterion	1.335420
Sum squared resid	59.78586	Schwarz criterion	1.390199
Log likelihood	-169.6045	Hannan-Quinn criter.	1.357442
Restr. log likelihood	-179.1090	Avg. log likelihood	-0.652325
LR statistic (3 df)	19.00891	McFadden R-squared	0.053065
Probability(LR stat)	0.000272		
Obs with Dep=0	142	Total obs	260
Obs with Dep=1	118		

RX program for the MT Whites

Dependent Variable: VOTERXPRGM
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 23:26
Sample(adjusted): 2 272
Included observations: 219
Excluded observations: 52 after adjusting endpoints
Convergence achieved after 3 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.956570	0.212320	4.505331	0.0000
RXBID	-0.003502	0.000946	-3.703512	0.0002

Mean dependent var	0.593607	S.D. dependent var	0.492285
S.E. of regression	0.477177	Akaike info criterion	1.303277
Sum squared resid	49.41040	Schwarz criterion	1.334228
Log likelihood	-140.7089	Hannan-Quinn criter.	1.315777
Restr. log likelihood	-147.9386	Avg. log likelihood	-0.642506
LR statistic (1 df)	14.45946	McFadden R-squared	0.048870
Probability(LR stat)	0.000143		

Obs with Dep=0	89	Total obs	219
Obs with Dep=1	130		

Mech program for the MT Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 23:23
Sample(adjusted): 1 272
Included observations: 265
Excluded observations: 7 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.169898	0.193764	-0.876829	0.3806
MECHBID	-0.003329	0.001008	-3.303312	0.0010

Mean dependent var	0.335849	S.D. dependent var	0.473180
S.E. of regression	0.462893	Akaike info criterion	1.245308
Sum squared resid	56.35301	Schwarz criterion	1.272324
Log likelihood	-163.0033	Hannan-Quinn criter.	1.256163
Restr. log likelihood	-169.1346	Avg. log likelihood	-0.615107
LR statistic (1 df)	12.26265	McFadden R-squared	0.036251
Probability(LR stat)	0.000462		

Obs with Dep=0	176	Total obs	265
Obs with Dep=1	89		

RX program or the CA Hispanics

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 23:31
Sample(adjusted): 1 306
Included observations: 276
Excluded observations: 30 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.225258	0.932575	3.458445	0.0005
RXBID	-0.001619	0.001069	-1.514047	0.1300
EDUC	-0.125873	0.071242	-1.766844	0.0773
EXPSMOKE	0.567245	0.358202	1.583588	0.1133

Mean dependent var	0.833333	S.D. dependent var	0.373355
S.E. of regression	0.369495	Akaike info criterion	0.900859
Sum squared resid	37.13531	Schwarz criterion	0.953328
Log likelihood	-120.3185	Hannan-Quinn criter.	0.921914
Restr. log likelihood	-124.3549	Avg. log likelihood	-0.435937
LR statistic (3 df)	8.072798	McFadden R-squared	0.032459
Probability(LR stat)	0.044531		

Obs with Dep=0	46	Total obs	276
Obs with Dep=1	230		

Mech program the CA Hispanics

RX program or the FL Hispanics

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 23:35
Sample(adjusted): 3 340
Included observations: 277
Excluded observations: 61 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.150849	0.196568	5.854723	0.0000
RXBID	-0.003467	0.001168	-2.968625	0.0030

Mean dependent var	0.675090	S.D. dependent var	0.469189
S.E. of regression	0.462447	Akaike info criterion	1.243568
Sum squared resid	58.81073	Schwarz criterion	1.269734
Log likelihood	-170.2342	Hannan-Quinn criter.	1.254067
Restr. log likelihood	-174.6527	Avg. log likelihood	-0.614564
LR statistic (1 df)	8.837024	McFadden R-squared	0.025299
Probability(LR stat)	0.002952		
Obs with Dep=0	90	Total obs	277
Obs with Dep=1	187		

Mech program the FL Hispanics

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/09/04 Time: 23:39
Sample(adjusted): 2 342
Included observations: 292
Excluded observations: 49 after adjusting endpoints
Convergence achieved after 5 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.339505	1.104590	3.023298	0.0025
MECHBID	-0.001976	0.001063	-1.858630	0.0631
EDUC	-0.217423	0.075422	-2.882761	0.0039

Mean dependent var	0.496575	S.D. dependent var	0.500847
S.E. of regression	0.492908	Akaike info criterion	1.368208
Sum squared resid	70.21481	Schwarz criterion	1.405983
Log likelihood	-196.7584	Hannan-Quinn criter.	1.383339
Restr. log likelihood	-202.3921	Avg. log likelihood	-0.673830
LR statistic (2 df)	11.26746	McFadden R-squared	0.027836
Probability(LR stat)	0.003575		
Obs with Dep=0	147	Total obs	292
Obs with Dep=1	145		

APPENDIX 7: **Three state pooled data regressions for 2 programs with state variables** (Protest responses excluded)

RX program without income variable for the Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 12:11
Sample(adjusted): 1 694
Included observations: 610
Excluded observations: 84 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.552391	0.813472	3.137649	0.0017
AGE	-0.006322	0.006348	-0.995810	0.3193
CA	1.212937	0.440949	2.750742	0.0059
CABID	-0.001906	0.001757	-1.084693	0.2781
EDUC	-0.107358	0.048624	-2.207922	0.0272
EXPSMOKE	0.258968	0.293130	0.883456	0.3770
FL	0.749253	0.343618	2.180482	0.0292
FLBID	-0.002453	0.001720	-1.426715	0.1537
OWNHOME	0.234470	0.258603	0.906680	0.3646
RESPPROB	0.393816	0.248105	1.587294	0.1124
RXBID	-0.004001	0.001013	-3.947747	0.0001
WITNESSFIRE	0.060666	0.239501	0.253300	0.8000

Mean dependent var	0.722951	S.D. dependent var	0.447908
S.E. of regression	0.424589	Akaike info criterion	1.097047
Sum squared resid	107.8047	Schwarz criterion	1.183869
Log likelihood	-322.5994	Hannan-Quinn criter.	1.130820
Restr. log likelihood	-359.9883	Avg. log likelihood	-0.528851
LR statistic (11 df)	74.77779	McFadden R-squared	0.103861
Probability(LR stat)	1.50E-11		
Obs with Dep=0	169	Total obs	610
Obs with Dep=1	441		

RX program with income variable for the Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 12:12
Sample(adjusted): 1 694
Included observations: 552
Excluded observations: 142 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.696246	0.856777	3.146964	0.0016
AGE	-0.003271	0.006881	-0.475412	0.6345
CA	1.234658	0.463075	2.666215	0.0077
CABID	-0.002425	0.001839	-1.318413	0.1874
EDUC	-0.133597	0.053202	-2.511115	0.0120
EXPSMOKE	0.263658	0.318024	0.829049	0.4071
FL	0.645807	0.359432	1.796746	0.0724
FLBID	-0.001224	0.001894	-0.646028	0.5183
OWNHOME	0.157819	0.284379	0.554958	0.5789
RESPPROB	0.359817	0.260764	1.379858	0.1676
RXBID	-0.003931	0.001047	-3.756079	0.0002
WITNESSFIRE	0.010385	0.254396	0.040822	0.9674
INCOME	3.72E-06	3.32E-06	1.120821	0.2624

Mean dependent var	0.728261	S.D. dependent var	0.445260
S.E. of regression	0.423784	Akaike info criterion	1.099019
Sum squared resid	96.80061	Schwarz criterion	1.200606
Log likelihood	-290.3293	Hannan-Quinn criter.	1.138711
Restr. log likelihood	-322.9095	Avg. log likelihood	-0.525959
LR statistic (12 df)	65.16042	McFadden R-squared	0.100896
Probability(LR stat)	2.55E-09		
Obs with Dep=0	150	Total obs	552
Obs with Dep=1	402		

Mech program without income variable for the Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 15:14
Sample(adjusted): 1 710
Included observations: 675
Excluded observations: 35 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.135466	0.656470	0.206355	0.8365
AGE	-0.001768	0.005092	-0.347154	0.7285
CA	0.181267	0.333576	0.543406	0.5869
CABID	0.001591	0.001562	1.018247	0.3086
EXPSMOKE	-0.218189	0.243980	-0.894291	0.3712
EDUC	0.027395	0.040150	0.682303	0.4950
FL	0.306271	0.284996	1.074650	0.2825
FLBID	-0.001593	0.001668	-0.955186	0.3395
MECHBID	-0.003593	0.001041	-3.453051	0.0006
OWNHOME	-0.095178	0.208061	-0.457454	0.6473
RESPPROB	0.104318	0.197801	0.527387	0.5979
WITNESSFIRE	-0.083903	0.194723	-0.430884	0.6666

Mean dependent var	0.454815	S.D. dependent var	0.498323
S.E. of regression	0.486329	Akaike info criterion	1.349367
Sum squared resid	156.8101	Schwarz criterion	1.429629
Log likelihood	-443.4114	Hannan-Quinn criter.	1.380445
Restr. log likelihood	-465.1143	Avg. log likelihood	-0.656906
LR statistic (11 df)	43.40574	McFadden R-squared	0.046661
Probability(LR stat)	9.23E-06		
Obs with Dep=0	368	Total obs	675
Obs with Dep=1	307		

Mech program with income variable for the Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 15:15
Sample(adjusted): 1 710
Included observations: 606
Excluded observations: 104 after adjusting endpoints
Convergence achieved after 6 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.460102	0.704275	0.653299	0.5136
AGE	0.003164	0.005591	0.565944	0.5714
CA	0.133685	0.353364	0.378320	0.7052
CABID	0.001339	0.001625	0.824432	0.4097
EXPSMOKE	-0.324892	0.262225	-1.238984	0.2154
EDUC	-0.017281	0.044154	-0.391385	0.6955
FL	0.194588	0.301409	0.645593	0.5185
FLBID	-0.000382	0.001779	-0.214617	0.8301
MECHBID	-0.003661	0.001071	-3.418569	0.0006
OWNHOME	-0.192290	0.230923	-0.832703	0.4050
RESPPROB	0.085613	0.208116	0.411373	0.6808
WITNESSFIRE	-0.081842	0.206630	-0.396079	0.6920
INCOME	6.06E-06	2.73E-06	2.217797	0.0266

Mean dependent var	0.468647	S.D. dependent var	0.499428
S.E. of regression	0.487161	Akaike info criterion	1.356769
Sum squared resid	140.7344	Schwarz criterion	1.451306
Log likelihood	-398.1010	Hannan-Quinn criter.	1.393554
Restr. log likelihood	-418.8550	Avg. log likelihood	-0.656932
LR statistic (12 df)	41.50799	McFadden R-squared	0.049549
Probability(LR stat)	4.03E-05		
Obs with Dep=0	322	Total obs	606
Obs with Dep=1	284		

RX program without income variable for the Hispanics

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 15:20
Sample(adjusted): 1 581
Included observations: 505
Excluded observations: 76 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.450127	0.958782	3.598446	0.0003
AGE	-0.005482	0.007726	-0.709532	0.4780
CA	0.356218	0.377215	0.944336	0.3450
CARXBID	0.001911	0.001707	1.119483	0.2629
EXPSMOKE	0.357896	0.274562	1.303513	0.1924
EDUC	-0.122525	0.059120	-2.072491	0.0382
RXBID	-0.004232	0.001287	-3.287247	0.0010
OWNHOME	-0.246070	0.257434	-0.955855	0.3391
RESPPROB	0.055690	0.309643	0.179851	0.8573
WITNESSFIRE	0.089457	0.284007	0.314981	0.7528

Mean dependent var	0.792079	S.D. dependent var	0.406222
S.E. of regression	0.395541	Akaike info criterion	0.994846
Sum squared resid	77.44425	Schwarz criterion	1.078501
Log likelihood	-241.1986	Hannan-Quinn criter.	1.027658
Restr. log likelihood	-258.1504	Avg. log likelihood	-0.477621
LR statistic (9 df)	33.90348	McFadden R-squared	0.065666
Probability(LR stat)	9.29E-05		
Obs with Dep=0	105	Total obs	505
Obs with Dep=1	400		

RX program with income variable for the Hispanics

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 15:40
Sample(adjusted): 1 540
Included observations: 458
Excluded observations: 82 after adjusting endpoints
Convergence achieved after 6 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.196372	1.002034	3.189883	0.0014
AGE	-0.005112	0.008219	-0.621943	0.5340
CA	0.553731	0.391741	1.413511	0.1575
CARXBID	0.001881	0.001767	1.064448	0.2871
EXPSMOKE	0.255468	0.281760	0.906687	0.3646
EDUC	-0.133221	0.063847	-2.086582	0.0369
RXBID	-0.004265	0.001340	-3.182283	0.0015
OWNHOME	-0.300263	0.274738	-1.092906	0.2744
RESPPROB	0.054572	0.318928	0.171110	0.8641
WITNESSFIRE	0.199954	0.295423	0.676842	0.4985
INCOME	6.77E-06	5.83E-06	1.161367	0.2455

Mean dependent var	0.775109	S.D. dependent var	0.417967
S.E. of regression	0.402960	Akaike info criterion	1.026489
Sum squared resid	72.58251	Schwarz criterion	1.125606
Log likelihood	-224.0660	Hannan-Quinn criter.	1.065526
Restr. log likelihood	-244.1272	Avg. log likelihood	-0.489227
LR statistic (10 df)	40.12231	McFadden R-squared	0.082175
Probability(LR stat)	1.61E-05		
Obs with Dep=0	103	Total obs	458
Obs with Dep=1	355		

Mech program without income variable for the Hispanics

Dependent Variable: VOTEMECHPRGM
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 15:18
Sample(adjusted): 1 557
Included observations: 531
Excluded observations: 26 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.343779	0.799176	4.184035	0.0000
AGE	0.003248	0.006601	0.491999	0.6227
CA	-0.164388	0.304862	-0.539222	0.5897
CAMECHBID	0.002355	0.001437	1.639303	0.1012
EXPSMOKE	0.103945	0.222941	0.466244	0.6410
EDUC	-0.196901	0.048645	-4.047690	0.0001
MECHBID	-0.002841	0.001144	-2.483674	0.0130
OWNHOME	-0.100295	0.209242	-0.479327	0.6317
RESPPROB	-0.098674	0.248721	-0.396725	0.6916
WITNESSFIRE	0.126795	0.232082	0.546337	0.5848

Mean dependent var	0.640301	S.D. dependent var	0.480365
S.E. of regression	0.470040	Akaike info criterion	1.282912
Sum squared resid	115.1087	Schwarz criterion	1.363416
Log likelihood	-330.6131	Hannan-Quinn criter.	1.314420
Restr. log likelihood	-346.8729	Avg. log likelihood	-0.622624
LR statistic (9 df)	32.51962	McFadden R-squared	0.046875
Probability(LR stat)	0.000162		
Obs with Dep=0	191	Total obs	531
Obs with Dep=1	340		

Mech program with income variable for the Hispanics

Dependent Variable: VOTEMECHPRGM
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 15:17
Sample(adjusted): 1 523
Included observations: 487
Excluded observations: 36 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.903196	0.829548	3.499731	0.0005
AGE	0.003312	0.007063	0.468897	0.6391
CA	0.107715	0.318742	0.337936	0.7354
CAMECHBID	0.002200	0.001508	1.458710	0.1446
EXPSMOKE	-0.013758	0.230672	-0.059645	0.9524
EDUC	-0.181852	0.051951	-3.500466	0.0005
MECHBID	-0.002994	0.001223	-2.448717	0.0143
OWNHOME	-0.180645	0.225178	-0.802232	0.4224
RESPPROB	-0.183153	0.259739	-0.705142	0.4807
WITNESSFIRE	0.215307	0.243313	0.884897	0.3762
INCOME	3.13E-06	4.48E-06	0.697591	0.4854

Mean dependent var	0.616016	S.D. dependent var	0.486854
S.E. of regression	0.473706	Akaike info criterion	1.300606
Sum squared resid	106.8133	Schwarz criterion	1.395208
Log likelihood	-305.6976	Hannan-Quinn criter.	1.33776
Restr. log likelihood	-324.3326	Avg. log likelihood	-0.62771
LR statistic (10 df)	37.26988	McFadden R-squared	0.057456
Probability(LR stat)	5.08E-05		
Obs with Dep=0	187	Total obs	487
Obs with Dep=1	300		

APPENDIX 8: **Regressions for 2 programs for white and Hispanic people in each state** (Protest responses excluded)

RX program without income variable for the CA Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/11/04 Time: 22:19
Sample(adjusted): 1 155
Included observations: 152
Excluded observations: 3 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.231197	1.543821	0.797500	0.4252
AGE	0.002304	0.014378	0.160249	0.8727
EDUC	0.044568	0.093507	0.476622	0.6336
EXPSMOKE	-0.162443	0.505385	-0.321425	0.7479
OWNHOME	-0.061503	0.537391	-0.114447	0.9089
RESPPROB	0.140288	0.572488	0.245050	0.8064
RXBID	-0.005637	0.001453	-3.879876	0.0001
WITNESSFIRE	0.614766	0.487322	1.261520	0.2071

Mean dependent var	0.776316	S.D. dependent var	0.418090
S.E. of regression	0.401019	Akaike info criterion	1.043052
Sum squared resid	23.15753	Schwarz criterion	1.202204
Log likelihood	-71.27197	Hannan-Quinn criter.	1.107705
Restr. log likelihood	-80.79280	Avg. log likelihood	-0.468895
LR statistic (7 df)	19.04166	McFadden R-squared	0.117843
Probability(LR stat)	0.008058		

Obs with Dep=0	34	Total obs	152
Obs with Dep=1	118		

RX program with income variable for the CA whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/11/04 Time: 22:21
Sample(adjusted): 1 155
Included observations: 145
Excluded observations: 10 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.222022	1.602361	0.762639	0.4457
AGE	0.011778	0.016689	0.705707	0.4804
EDUC	-0.000527	0.101259	-0.005209	0.9958
EXPSMOKE	-0.143190	0.521832	-0.274398	0.7838
OWNHOME	-0.208668	0.619569	-0.336796	0.7363
RESPPROB	0.205662	0.593537	0.346502	0.7290
RXBID	-0.006199	0.001556	-3.983849	0.0001
WITNESSFIRE	0.614545	0.497652	1.234889	0.2169
INCOME	5.92E-06	6.12E-06	0.966979	0.3336

Mean dependent var	0.779310	S.D. dependent var	0.416149
S.E. of regression	0.394635	Akaike info criterion	1.032426
Sum squared resid	21.18015	Schwarz criterion	1.217189
Log likelihood	-65.85091	Hannan-Quinn criter.	1.107502
Restr. log likelihood	-76.52802	Avg. log likelihood	-0.454144
LR statistic (8 df)	21.35422	McFadden R-squared	0.139519
Probability(LR stat)	0.006264		

Obs with Dep=0	32	Total obs	145
Obs with Dep=1	113		

Mech program without income variable for the CA Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/11/04 Time: 22:34
Sample(adjusted): 1 174
Included observations: 165
Excluded observations: 9 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-1.679794	1.234955	-1.360207	0.1738
AGE	0.007241	0.011131	0.650541	0.5153
EDUC	0.133080	0.073992	1.798591	0.0721
EXPSMOKE	-0.848203	0.436685	-1.942366	0.0521
OWNHOME	-0.439535	0.407746	-1.077963	0.2811
RESPPROB	0.523563	0.438895	1.192911	0.2329
MECHBID	-0.001726	0.001199	-1.439138	0.1501
WITNESSFIRE	0.763557	0.419372	1.820714	0.0687

Mean dependent var	0.515152	S.D. dependent var	0.501292
S.E. of regression	0.491366	Akaike info criterion	1.401424
Sum squared resid	37.90616	Schwarz criterion	1.552016
Log likelihood	-107.6175	Hannan-Quinn criter.	1.462555
Restr. log likelihood	-114.2935	Avg. log likelihood	-0.652227
LR statistic (7 df)	13.35201	McFadden R-squared	0.058411
Probability(LR stat)	0.063982		
Obs with Dep=0	80	Total obs	165
Obs with Dep=1	85		

Mech program with income variable for the CA Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/11/04 Time: 22:32
Sample(adjusted): 1 173
Included observations: 156
Excluded observations: 17 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-1.521178	1.281454	-1.187072	0.2352
AGE	0.021578	0.012808	1.684688	0.0920
EDUC	0.083743	0.078814	1.062532	0.2880
EXPSMOKE	-1.004660	0.450747	-2.228875	0.0258
OWNHOME	-0.611278	0.478870	-1.276500	0.2018
RESPPROB	0.466401	0.447766	1.041619	0.2976
MECHBID	-0.002157	0.001267	-1.701861	0.0888
WITNESSFIRE	0.596596	0.426540	1.398685	0.1619
INCOME	5.27E-06	4.50E-06	1.170756	0.2417

Mean dependent var	0.538462	S.D. dependent var	0.500124
S.E. of regression	0.488326	Akaike info criterion	1.396638
Sum squared resid	35.05388	Schwarz criterion	1.572591
Log likelihood	-99.93773	Hannan-Quinn criter.	1.468102
Restr. log likelihood	-107.6690	Avg. log likelihood	-0.640626
LR statistic (8 df)	15.46247	McFadden R-squared	0.071806
Probability(LR stat)	0.050753		
Obs with Dep=0	72	Total obs	156
Obs with Dep=1	84		

RX program without income variable for the FL Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 00:58
Sample(adjusted): 1 292
Included observations: 259
Excluded observations: 33 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	4.839033	1.402122	3.451221	0.0006
AGE	-0.010122	0.009818	-1.030920	0.3026
EDU	-0.232848	0.083933	-2.774216	0.0055
EXPSMOKE	0.585023	0.433332	1.350057	0.1770
RXBID	-0.006988	0.001468	-4.760537	0.0000
OWNHOME	0.831837	0.408944	2.034109	0.0419
RESPPROB	0.890700	0.417048	2.135724	0.0327
WITNESSFIRE	-0.275921	0.363098	-0.759908	0.4473

Mean dependent var	0.752896	S.D. dependent var	0.432163
S.E. of regression	0.406347	Akaike info criterion	1.033047
Sum squared resid	41.44458	Schwarz criterion	1.142911
Log likelihood	-125.7796	Hannan-Quinn criter.	1.077219
Restr. log likelihood	-144.8150	Avg. log likelihood	-0.485636
LR statistic (7 df)	38.07084	McFadden R-squared	0.131446
Probability(LR stat)	2.94E-06		
Obs with Dep=0	64	Total obs	259
Obs with Dep=1	195		

RX program with income variable for the FL whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 00:59
Sample(adjusted): 10 287
Included observations: 214
Excluded observations: 64 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	5.507490	1.587200	3.469940	0.0005
AGE	-0.006707	0.011253	-0.596042	0.5511
EDU	-0.299079	0.097585	-3.064809	0.0022
EXPSMOKE	0.689099	0.511785	1.346462	0.1782
RXBID	-0.005358	0.001656	-3.235527	0.0012
OWNHOME	0.768966	0.463834	1.657848	0.0973
RESPPROB	0.747501	0.466151	1.603559	0.1088
WITNESSFIRE	-0.484089	0.417927	-1.158308	0.2467
INCOME	3.28E-06	5.72E-06	0.573613	0.5662

Mean dependent var	0.771028	S.D. dependent var	0.421156
S.E. of regression	0.401988	Akaike info criterion	1.030769
Sum squared resid	33.12684	Schwarz criterion	1.172329
Log likelihood	-101.2923	Hannan-Quinn criter.	1.087972
Restr. log likelihood	-115.1387	Avg. log likelihood	-0.473329
LR statistic (8 df)	27.69269	McFadden R-squared	0.120258
Probability(LR stat)	0.000536		
Obs with Dep=0	49	Total obs	214
Obs with Dep=1	165		

Mech program without income variable for the FL Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 01:09
Sample(adjusted): 1 297
Included observations: 284
Excluded observations: 13 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.886525	1.163688	2.480498	0.0131
AGE	-0.008201	0.007689	-1.066530	0.2862
EDU	-0.110750	0.071220	-1.555039	0.1199
EXPSMOKE	0.013617	0.358486	0.037986	0.9697
MECHBID	-0.005418	0.001347	-4.021236	0.0001
OWNHOME	0.058548	0.333438	0.175590	0.8606
RESPPROB	-0.025620	0.301951	-0.084847	0.9324
WITNESSFIRE	-0.604621	0.277912	-2.175584	0.0296

Mean dependent var	0.475352	S.D. dependent var	0.500274
S.E. of regression	0.482448	Akaike info criterion	1.345103
Sum squared resid	64.24059	Schwarz criterion	1.447891
Log likelihood	-183.0046	Hannan-Quinn criter.	1.386313
Restr. log likelihood	-196.5086	Avg. log likelihood	-0.644382
LR statistic (7 df)	27.00799	McFadden R-squared	0.068720
Probability(LR stat)	0.000332		

Obs with Dep=0	149	Total obs	284
Obs with Dep=1	135		

Mech program with income variable for the FL Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 01:10
Sample(adjusted): 1 294
Included observations: 232
Excluded observations: 62 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.126016	1.324207	2.360670	0.0182
AGE	-0.004876	0.008878	-0.549220	0.5829
EDU	-0.167282	0.082437	-2.029204	0.0424
EXPSMOKE	0.004562	0.403643	0.011303	0.9910
MECHBID	-0.004034	0.001462	-2.758608	0.0058
OWNHOME	0.023870	0.374590	0.063722	0.9492
RESPPROB	-0.110380	0.334704	-0.329785	0.7416
WITNESSFIRE	-0.545659	0.304650	-1.791104	0.0733
INCOME	7.18E-06	4.71E-06	1.524166	0.1275

Mean dependent var	0.495690	S.D. dependent var	0.501062
S.E. of regression	0.489328	Akaike info criterion	1.383382
Sum squared resid	53.39556	Schwarz criterion	1.517091
Log likelihood	-151.4723	Hannan-Quinn criter.	1.437305
Restr. log likelihood	-160.8015	Avg. log likelihood	-0.652898
LR statistic (8 df)	18.65854	McFadden R-squared	0.058017
Probability(LR stat)	0.016796		

Obs with Dep=0	117	Total obs	232
Obs with Dep=1	115		

RX program without income variable for the MT Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/11/04 Time: 22:16
Sample(adjusted): 1 201
Included observations: 199
Excluded observations: 2 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.038890	1.394957	2.178483	0.0294
AGE	-0.005765	0.010950	-0.526460	0.5986
EDUC	-0.110643	0.078413	-1.411021	0.1582
EXPSMOKE	0.158257	0.794351	0.199228	0.8421
OWNHOME	-0.199777	0.446783	-0.447145	0.6548
RESPPROB	0.102937	0.389246	0.264452	0.7914
RXBID	-0.004035	0.001020	-3.956031	0.0001
WITNESSFIRE	0.118010	0.454078	0.259889	0.7949

Mean dependent var	0.643216	S.D. dependent var	0.480258
S.E. of regression	0.464137	Akaike info criterion	1.281045
Sum squared resid	41.14577	Schwarz criterion	1.413439
Log likelihood	-119.4640	Hannan-Quinn criter.	1.334629
Restr. log likelihood	-129.6575	Avg. log likelihood	-0.600322
LR statistic (7 df)	20.38703	McFadden R-squared	0.078619
Probability(LR stat)	0.004792		
Obs with Dep=0	71	Total obs	199
Obs with Dep=1	128		

RX program with income variable for the MT whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/11/04 Time: 22:15
Sample(adjusted): 1 201
Included observations: 193
Excluded observations: 8 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.012282	1.410573	2.135503	0.0327
AGE	-0.007079	0.010962	-0.645764	0.5184
EDUC	-0.113646	0.083482	-1.361329	0.1734
EXPSMOKE	0.104613	0.791752	0.132128	0.8949
INCOME	3.90E-06	6.09E-06	0.640475	0.5219
OWNHOME	-0.275811	0.463809	-0.594665	0.5521
RESPPROB	0.159207	0.392882	0.405229	0.6853
RXBID	-0.003954	0.001051	-3.760737	0.0002
WITNESSFIRE	0.147456	0.456562	0.322969	0.7467

Mean dependent var	0.642487	S.D. dependent var	0.480514
S.E. of regression	0.466967	Akaike info criterion	1.299931
Sum squared resid	40.12276	Schwarz criterion	1.452077
Log likelihood	-116.4433	Hannan-Quinn criter.	1.361545
Restr. log likelihood	-125.8309	Avg. log likelihood	-0.603333
LR statistic (8 df)	18.77529	McFadden R-squared	0.074605
Probability(LR stat)	0.016109		
Obs with Dep=0	69	Total obs	193
Obs with Dep=1	124		

Mech program without income variable for the MT Whites

Dependent Variable: VOTEMECPGM
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 01:33
Sample(adjusted): 1 229
Included observations: 226
Excluded observations: 3 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.828032	1.256667	-0.658912	0.5100
AGE	0.000734	0.009243	0.079430	0.9367
EXPSMOKE	-0.054340	0.771085	-0.070472	0.9438
OWNHOME	-0.084367	0.381751	-0.220999	0.8251
RESPPROB	0.056596	0.349210	0.162068	0.8713
MECHBID	-0.003532	0.001052	-3.358312	0.0008
WITNESSFIRE	0.212988	0.419073	0.508237	0.6113
EDUC	0.058016	0.068657	0.845005	0.3981

Mean dependent var	0.384956	S.D. dependent var	0.487665
S.E. of regression	0.479742	Akaike info criterion	1.341937
Sum squared resid	50.17319	Schwarz criterion	1.463018
Log likelihood	-143.6389	Hannan-Quinn criter.	1.390801
Restr. log likelihood	-150.6150	Avg. log likelihood	-0.635570
LR statistic (7 df)	13.95222	McFadden R-squared	0.046318
Probability(LR stat)	0.052038		

Obs with Dep=0	139	Total obs	226
Obs with Dep=1	87		

Mech program with income variable for the MT Whites

Dependent Variable: VOTEMECPGM
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 01:34
Sample(adjusted): 1 229
Included observations: 218
Excluded observations: 11 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.012779	1.323353	0.009657	0.9923
AGE	-0.000627	0.009441	-0.066451	0.9470
EXPSMOKE	-0.071835	0.772685	-0.092968	0.9259
OWNHOME	-0.198713	0.398624	-0.498498	0.6181
RESPPROB	0.107292	0.355619	0.301706	0.7629
MECHBID	-0.003581	0.001090	-3.285558	0.0010
WITNESSFIRE	0.173345	0.426034	0.406880	0.6841
EDUC	-0.018206	0.076772	-0.237146	0.8125
INCOME	1.00E-05	5.99E-06	1.676677	0.0936

Mean dependent var	0.389908	S.D. dependent var	0.488852
S.E. of regression	0.480368	Akaike info criterion	1.348892
Sum squared resid	48.22746	Schwarz criterion	1.488619
Log likelihood	-138.0293	Hannan-Quinn criter.	1.405330
Restr. log likelihood	-145.7781	Avg. log likelihood	-0.633162
LR statistic (8 df)	15.49775	McFadden R-squared	0.053155
Probability(LR stat)	0.050160		

Obs with Dep=0	133	Total obs	218
Obs with Dep=1	85		

RX program without income variable for the CA Hispanics

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/11/04 Time: 22:24
Sample(adjusted): 1 301
Included observations: 262
Excluded observations: 39 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	4.396545	1.211515	3.628965	0.0003
AGE	-0.006886	0.013464	-0.511436	0.6090
EDUC	-0.148504	0.078374	-1.894821	0.0581
EXPSMOKE	0.626335	0.465149	1.346524	0.1781
OWNHOME	-0.444142	0.370384	-1.199139	0.2305
RESPPROB	-0.523493	0.492560	-1.062801	0.2879
RXBID	-0.002536	0.001159	-2.188600	0.0286
WITNESSFIRE	-0.218194	0.502768	-0.433985	0.6643

Mean dependent var	0.851145	S.D. dependent var	0.356627
S.E. of regression	0.351004	Akaike info criterion	0.851489
Sum squared resid	31.29372	Schwarz criterion	0.960447
Log likelihood	-103.5451	Hannan-Quinn criter.	0.895282
Restr. log likelihood	-110.2281	Avg. log likelihood	-0.395210
LR statistic (7 df)	13.36586	McFadden R-squared	0.060628
Probability(LR stat)	0.063680		
Obs with Dep=0	39	Total obs	262
Obs with Dep=1	223		

RX program with income variable for the CA Hispanics

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/11/04 Time: 22:23
Sample(adjusted): 1 301
Included observations: 250
Excluded observations: 51 after adjusting endpoints
Convergence achieved after 6 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	4.071864	1.266198	3.215818	0.0013
AGE	-0.002778	0.014621	-0.190012	0.8493
EDUC	-0.128489	0.086896	-1.478639	0.1392
EXPSMOKE	0.630188	0.484651	1.300292	0.1935
OWNHOME	-0.321430	0.390715	-0.822670	0.4107
RESPPROB	-0.600321	0.497129	-1.207576	0.2272
RXBID	-0.002346	0.001201	-1.954091	0.0507
WITNESSFIRE	-0.131371	0.534012	-0.246008	0.8057
INCOME	-5.00E-06	7.22E-06	-0.693098	0.4882

Mean dependent var	0.852000	S.D. dependent var	0.355812
S.E. of regression	0.349524	Akaike info criterion	0.856870
Sum squared resid	29.44233	Schwarz criterion	0.983643
Log likelihood	-98.10879	Hannan-Quinn criter.	0.907893
Restr. log likelihood	-104.8060	Avg. log likelihood	-0.392435
LR statistic (8 df)	13.39448	McFadden R-squared	0.063901
Probability(LR stat)	0.098978		
Obs with Dep=0	37	Total obs	250
Obs with Dep=1	213		

Mech program without income variable for the CA Hispanics

Dependent Variable: VOTEMECHPRGM
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/11/04 Time: 22:45
Sample(adjusted): 1 303
Included observations: 286
Excluded observations: 17 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.693348	0.914671	2.944607	0.0032
AGE	0.013099	0.010456	1.252688	0.2103
EDUC	-0.183737	0.061891	-2.968740	0.0030
EXPSMOKE	0.146808	0.334107	0.439405	0.6604
OWNHOME	-0.211887	0.276633	-0.765947	0.4437
RESPPROB	-0.577386	0.366545	-1.575213	0.1152
MECHBID	-0.000501	0.000886	-0.565558	0.5717
WITNESSFIRE	0.362509	0.376557	0.962692	0.3357

Mean dependent var	0.692308	S.D. dependent var	0.462347
S.E. of regression	0.452921	Akaike info criterion	1.223741
Sum squared resid	57.02815	Schwarz criterion	1.326006
Log likelihood	-166.9949	Hannan-Quinn criter.	1.264732
Restr. log likelihood	-176.5311	Avg. log likelihood	-0.583898
LR statistic (7 df)	19.07251	McFadden R-squared	0.054020
Probability(LR stat)	0.007963		

Obs with Dep=0	88	Total obs	286
Obs with Dep=1	198		

Mech program with income variable for the CA Hispanics

Dependent Variable: VOTEMECHPRGM
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/11/04 Time: 22:43
Sample(adjusted): 1 303
Included observations: 273
Excluded observations: 30 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.546615	0.956251	2.663124	0.0077
AGE	0.016653	0.011292	1.474726	0.1403
EDUC	-0.178931	0.067743	-2.641328	0.0083
EXPSMOKE	0.128082	0.343694	0.372662	0.7094
OWNHOME	-0.220150	0.299378	-0.735356	0.4621
RESPPROB	-0.664143	0.372401	-1.783407	0.0745
MECHBID	-0.000742	0.000908	-0.816842	0.4140
WITNESSFIRE	0.362820	0.390612	0.928849	0.3530
INCOME	9.32E-07	5.72E-06	0.162990	0.8705

Mean dependent var	0.692308	S.D. dependent var	0.462386
S.E. of regression	0.453153	Akaike info criterion	1.229409
Sum squared resid	54.21190	Schwarz criterion	1.348403
Log likelihood	-158.8144	Hannan-Quinn criter.	1.277176
Restr. log likelihood	-168.5070	Avg. log likelihood	-0.581738
LR statistic (8 df)	19.38521	McFadden R-squared	0.057521
Probability(LR stat)	0.012930		

Obs with Dep=0	84	Total obs	273
Obs with Dep=1	189		

RX program without income variable for the FL Hispanics

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 00:28
Sample(adjusted): 1 280
Included observations: 243
Excluded observations: 37 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.469549	1.395086	1.770176	0.0767
AGE	-0.006264	0.009702	-0.645644	0.5185
EDU	-0.066618	0.092746	-0.718284	0.4726
EXPSMOKE	0.213669	0.345852	0.617806	0.5367
RXBID	-0.004082	0.001288	-3.168981	0.0015
OWNHOME	-0.032777	0.357198	-0.091763	0.9269
RESPPROB	0.349302	0.392530	0.889874	0.3735
WITNESSFIRE	0.232352	0.344879	0.673719	0.5005

Mean dependent var	0.728395	S.D. dependent var	0.445705
S.E. of regression	0.439322	Akaike info criterion	1.182365
Sum squared resid	45.35588	Schwarz criterion	1.297362
Log likelihood	-135.6573	Hannan-Quinn criter.	1.228685
Restr. log likelihood	-142.1182	Avg. log likelihood	-0.558260
LR statistic (7 df)	12.92185	McFadden R-squared	0.045462
Probability(LR stat)	0.074036		
Obs with Dep=0	66	Total obs	243
Obs with Dep=1	177		

RX program with income variable for the FL Hispanics

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 00:27
Sample(adjusted): 1 239
Included observations: 208
Excluded observations: 31 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.888353	1.478146	1.277515	0.2014
AGE	-0.005184	0.010515	-0.492957	0.6220
EDU	-0.079620	0.098328	-0.809739	0.4181
EXPSMOKE	-0.022248	0.369996	-0.060131	0.9521
RXBID	-0.004338	0.001371	-3.163448	0.0016
OWNHOME	-0.285033	0.392356	-0.726465	0.4676
RESPPROB	0.414666	0.409134	1.013522	0.3108
WITNESSFIRE	0.399869	0.368341	1.085595	0.2777
INCOME	2.32E-05	9.41E-06	2.467798	0.0136

Mean dependent var	0.682692	S.D. dependent var	0.466551
S.E. of regression	0.453050	Akaike info criterion	1.241240
Sum squared resid	40.84559	Schwarz criterion	1.385653
Log likelihood	-120.0890	Hannan-Quinn criter.	1.299633
Restr. log likelihood	-129.9633	Avg. log likelihood	-0.577351
LR statistic (8 df)	19.74853	McFadden R-squared	0.075977
Probability(LR stat)	0.011330		
Obs with Dep=0	66	Total obs	208
Obs with Dep=1	142		

Mech program without income variable for the FL Hispanics

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 00:16
Sample(adjusted): 1 254
Included observations: 245
Excluded observations: 9 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.807847	1.277259	2.981266	0.0029
AGE	-0.004863	0.008898	-0.546500	0.5847
EDU	-0.203755	0.082397	-2.472847	0.0134
EXPSMOKE	0.033290	0.306400	0.108647	0.9135
MECHBID	-0.002960	0.001155	-2.562018	0.0104
OWNHOME	-0.012637	0.329992	-0.038295	0.9695
RESPPROB	0.301583	0.338152	0.891858	0.3725
WITNESSFIRE	-0.073653	0.302075	-0.243824	0.8074

Mean dependent var	0.579592	S.D. dependent var	0.494635
S.E. of regression	0.488597	Akaike info criterion	1.374350
Sum squared resid	56.57824	Schwarz criterion	1.488677
Log likelihood	-160.3579	Hannan-Quinn criter.	1.420390
Restr. log likelihood	-166.7037	Avg. log likelihood	-0.654522
LR statistic (7 df)	12.69164	McFadden R-squared	0.038066
Probability(LR stat)	0.079988		
Obs with Dep=0	103	Total obs	245
Obs with Dep=1	142		

Mech program with income variable for the FL Hispanics

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 00:21
Sample(adjusted): 1 220
Included observations: 214
Excluded observations: 6 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.028320	1.317775	2.298056	0.0216
AGE	-0.007633	0.009740	-0.783693	0.4332
EDU	-0.160097	0.085264	-1.877663	0.0604
EXPSMOKE	-0.192706	0.321501	-0.599393	0.5489
MECHBID	-0.003085	0.001236	-2.496747	0.0125
OWNHOME	-0.133716	0.357743	-0.373777	0.7086
RESPPROB	0.257946	0.357367	0.721796	0.4704
WITNESSFIRE	0.065727	0.319785	0.205534	0.8372
INCOME	6.36E-06	7.52E-06	0.846013	0.3975

Mean dependent var	0.518692	S.D. dependent var	0.500822
S.E. of regression	0.497131	Akaike info criterion	1.417207
Sum squared resid	50.66352	Schwarz criterion	1.558767
Log likelihood	-142.6412	Hannan-Quinn criter.	1.474410
Restr. log likelihood	-148.1839	Avg. log likelihood	-0.666548
LR statistic (8 df)	11.08547	McFadden R-squared	0.037404
Probability(LR stat)	0.196903		
Obs with Dep=0	103	Total obs	214
Obs with Dep=1	111		

Appendix 9: **Three state pooled data regressions for 2 programs without state variables** (Protest responses excluded)

RX program without income variable for the Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 15:47
Sample(adjusted): 1 694
Included observations: 610
Excluded observations: 84 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.965397	0.795502	3.727704	0.0002
AGE	-0.004619	0.006253	-0.738740	0.4601
EXPSMOKE	0.042785	0.279291	0.153191	0.8782
EDUC	-0.083586	0.047264	-1.768500	0.0770
RXBID	-0.005150	0.000697	-7.387280	0.0000
OWNHOME	0.148240	0.254064	0.583476	0.5596
RESPPROB	0.349445	0.244082	1.431671	0.1522
WITNESSFIRE	0.014956	0.233502	0.064050	0.9489

Mean dependent var	0.722951	S.D. dependent var	0.447908
S.E. of regression	0.427533	Akaike info criterion	1.104094
Sum squared resid	110.0365	Schwarz criterion	1.161975
Log likelihood	-328.7486	Hannan-Quinn criter.	1.126609
Restr. log likelihood	-359.9883	Avg. log likelihood	-0.538932
LR statistic (7 df)	62.47929	McFadden R-squared	0.086780
Probability(LR stat)	4.82E-11		

Obs with Dep=0	169	Total obs	610
Obs with Dep=1	441		

RX program with income variable for the Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 15:48
Sample(adjusted): 1 694
Included observations: 552
Excluded observations: 142 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.072995	0.837816	3.667863	0.0002
AGE	-0.000435	0.006803	-0.063957	0.9490
EXPSMOKE	0.076099	0.305835	0.248825	0.8035
EDUC	-0.118128	0.052073	-2.268508	0.0233
RXBID	-0.004963	0.000738	-6.721512	0.0000
OWNHOME	0.005815	0.278318	0.020893	0.9833
RESPPROB	0.354437	0.257724	1.375258	0.1691
WITNESSFIRE	-0.056980	0.249026	-0.228812	0.8190
INCOME	5.86E-06	3.20E-06	1.833947	0.0667

Mean dependent var	0.728261	S.D. dependent var	0.445260
S.E. of regression	0.425940	Akaike info criterion	1.101609
Sum squared resid	98.51377	Schwarz criterion	1.171939
Log likelihood	-295.0442	Hannan-Quinn criter.	1.129089
Restr. log likelihood	-322.9095	Avg. log likelihood	-0.534500
LR statistic (8 df)	55.73055	McFadden R-squared	0.086294
Probability(LR stat)	3.18E-09		

Obs with Dep=0	150	Total obs	552
Obs with Dep=1	402		

Mech program without income variable for the Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 16:07
Sample(adjusted): 1 710
Included observations: 675
Excluded observations: 35 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.244237	0.647378	0.377271	0.7060
AGE	-0.001726	0.005063	-0.340834	0.7332
EDUC	0.038763	0.038580	1.004760	0.3150
EXPSMOKE	-0.321046	0.235991	-1.360417	0.1737
MECHBID	-0.003493	0.000653	-5.351431	0.0000
OWNHOME	-0.126889	0.205755	-0.616700	0.5374
RESPPROB	0.080149	0.195759	0.409426	0.6822
WITNESSFIRE	-0.098254	0.190166	-0.516673	0.6054

Mean dependent var	0.454815	S.D. dependent var	0.498323
S.E. of regression	0.487194	Akaike info criterion	1.348263
Sum squared resid	158.3175	Schwarz criterion	1.401771
Log likelihood	-447.0388	Hannan-Quinn criter.	1.368982
Restr. log likelihood	-465.1143	Avg. log likelihood	-0.662280
LR statistic (7 df)	36.15096	McFadden R-squared	0.038862
Probability(LR stat)	6.79E-06		
Obs with Dep=0	368	Total obs	675
Obs with Dep=1	307		

Mech program with income variable for the Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 16:07
Sample(adjusted): 1 710
Included observations: 606
Excluded observations: 104 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.491447	0.695156	0.706959	0.4796
AGE	0.003654	0.005557	0.657592	0.5108
EDUC	-0.009723	0.042902	-0.226642	0.8207
EXPSMOKE	-0.394779	0.256901	-1.536693	0.1244
MECHBID	-0.003347	0.000687	-4.870760	0.0000
OWNHOME	-0.233689	0.225368	-1.036920	0.2998
RESPPROB	0.085019	0.207062	0.410595	0.6814
WITNESSFIRE	-0.111941	0.202671	-0.552331	0.5807
INCOME	7.03E-06	2.62E-06	2.685228	0.0072

Mean dependent var	0.468647	S.D. dependent var	0.499428
S.E. of regression	0.486810	Akaike info criterion	1.348694
Sum squared resid	141.4795	Schwarz criterion	1.414142
Log likelihood	-399.6542	Hannan-Quinn criter.	1.374160
Restr. log likelihood	-418.8550	Avg. log likelihood	-0.659495
LR statistic (8 df)	38.40160	McFadden R-squared	0.045841
Probability(LR stat)	6.35E-06		
Obs with Dep=0	322	Total obs	606
Obs with Dep=1	284		

RX program without income variable for the Hispanics

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 15:57
Sample(adjusted): 1 581
Included observations: 505
Excluded observations: 76 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	4.469499	0.802226	5.571373	0.0000
AGE	-0.007836	0.007612	-1.029315	0.3033
EXPSMOKE	0.259531	0.269591	0.962686	0.3357
EDUC	-0.172635	0.053557	-3.223378	0.0013
RXBID	-0.002900	0.000828	-3.501962	0.0005
OWNHOME	-0.360231	0.251809	-1.430573	0.1526
RESPPROB	0.027069	0.306530	0.088306	0.9296
WITNESSFIRE	0.075114	0.282252	0.266124	0.7901

Mean dependent var	0.792079	S.D. dependent var	0.406222
S.E. of regression	0.398506	Akaike info criterion	1.000955
Sum squared resid	78.92706	Schwarz criterion	1.067878
Log likelihood	-244.7410	Hannan-Quinn criter.	1.027204
Restr. log likelihood	-258.1504	Avg. log likelihood	-0.484636
LR statistic (7 df)	26.81867	McFadden R-squared	0.051944
Probability(LR stat)	0.000359		

Obs with Dep=0	105	Total obs	505
Obs with Dep=1	400		

RX program with income variable for the Hispanics

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 15:58
Sample(adjusted): 1 540
Included observations: 458
Excluded observations: 82 after adjusting endpoints
Convergence achieved after 6 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	4.599500	0.821990	5.595569	0.0000
AGE	-0.007892	0.008059	-0.979334	0.3274
EXPSMOKE	0.158406	0.276560	0.572771	0.5668
EDUC	-0.206180	0.056685	-3.637303	0.0003
RXBID	-0.002950	0.000856	-3.446756	0.0006
OWNHOME	-0.475632	0.265389	-1.792210	0.0731
RESPPROB	0.028687	0.314251	0.091286	0.9273
WITNESSFIRE	0.140201	0.292438	0.479422	0.6316
INCOME	9.57E-06	5.70E-06	1.677314	0.0935

Mean dependent var	0.775109	S.D. dependent var	0.417967
S.E. of regression	0.408246	Akaike info criterion	1.039870
Sum squared resid	74.83241	Schwarz criterion	1.120966
Log likelihood	-229.1303	Hannan-Quinn criter.	1.071810
Restr. log likelihood	-244.1272	Avg. log likelihood	-0.500284
LR statistic (8 df)	29.99380	McFadden R-squared	0.061431
Probability(LR stat)	0.000212		

Obs with Dep=0	103	Total obs	458
Obs with Dep=1	355		

Mech program without income variable for the Hispanics

Dependent Variable: VOTEMECHPRGM
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 16:13
Sample(adjusted): 1 557
Included observations: 531
Excluded observations: 26 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.467295	0.659100	5.260648	0.0000
AGE	0.002754	0.006492	0.424218	0.6714
EDUC	-0.209513	0.045147	-4.640709	0.0000
EXPSMOKE	0.070275	0.221129	0.317803	0.7506
MECHBID	-0.001326	0.000687	-1.932050	0.0534
OWNHOME	-0.139980	0.204425	-0.684749	0.4935
RESPPROB	-0.122693	0.247464	-0.495801	0.6200
WITNESSFIRE	0.114684	0.231029	0.496404	0.6196

Mean dependent var	0.640301	S.D. dependent var	0.480365
S.E. of regression	0.470730	Akaike info criterion	1.281835
Sum squared resid	115.8899	Schwarz criterion	1.346239
Log likelihood	-332.3273	Hannan-Quinn criter.	1.307042
Restr. log likelihood	-346.8729	Avg. log likelihood	-0.625852
LR statistic (7 df)	29.09119	McFadden R-squared	0.041934
Probability(LR stat)	0.000139		

Obs with Dep=0	191	Total obs	531
Obs with Dep=1	340		

Mech program with income variable for the Hispanics

Dependent Variable: VOTEMECHPRGM
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 16:13
Sample(adjusted): 1 523
Included observations: 487
Excluded observations: 36 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.518160	0.675131	5.211081	0.0000
AGE	0.001822	0.006935	0.262791	0.7927
EDUC	-0.218267	0.047373	-4.607449	0.0000
EXPSMOKE	-0.052582	0.229126	-0.229489	0.8185
MECHBID	-0.001522	0.000711	-2.141870	0.0322
OWNHOME	-0.281206	0.217728	-1.291549	0.1965
RESPPROB	-0.205591	0.257816	-0.797433	0.4252
WITNESSFIRE	0.171211	0.241319	0.709481	0.4780
INCOME	4.76E-06	4.38E-06	1.088337	0.2764

Mean dependent var	0.616016	S.D. dependent var	0.486854
S.E. of regression	0.475631	Akaike info criterion	1.304098
Sum squared resid	108.1353	Schwarz criterion	1.381499
Log likelihood	-308.5479	Hannan-Quinn criter.	1.334504
Restr. log likelihood	-324.3326	Avg. log likelihood	-0.63356
LR statistic (8 df)	31.56934	McFadden R-squared	0.048668
Probability(LR stat)	0.000111		

Obs with Dep=0	187	Total obs	487
Obs with Dep=1	300		

APPENDIX 10: **Two state pooled data regression for two programs without state variable** (Protest responses excluded)

RX program without income variable for the CA-FL Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 15:51
Sample(adjusted): 1 471
Included observations: 411
Excluded observations: 60 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.252183	1.022911	3.179340	0.0015
AGE	-0.006921	0.007858	-0.880738	0.3785
EXPSMOKE	0.161787	0.311859	0.518784	0.6039
EDUC	-0.103098	0.061193	-1.684814	0.0920
RXBID	-0.005825	0.000982	-5.931435	0.0000
OWNHOME	0.428428	0.315726	1.356960	0.1748
RESPPROB	0.530056	0.324650	1.632699	0.1025
WITNESSFIRE	0.105891	0.281592	0.376043	0.7069

Mean dependent var	0.761557	S.D. dependent var	0.426651
S.E. of regression	0.408237	Akaike info criterion	1.032864
Sum squared resid	67.16307	Schwarz criterion	1.111085
Log likelihood	-204.2536	Hannan-Quinn criter.	1.063808
Restr. log likelihood	-225.7534	Avg. log likelihood	-0.496967
LR statistic (7 df)	42.99956	McFadden R-squared	0.095236
Probability(LR stat)	3.34E-07		

Obs with Dep=0	98	Total obs	411
Obs with Dep=1	313		

RX program with income variable for the CA-FL Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 15:50
Sample(adjusted): 1 466
Included observations: 359
Excluded observations: 107 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.442196	1.107531	3.107990	0.0019
AGE	5.92E-05	0.008973	0.006600	0.9947
EXPSMOKE	0.213920	0.347730	0.615191	0.5384
EDUC	-0.149501	0.068863	-2.170988	0.0299
RXBID	-0.005596	0.001067	-5.246455	0.0000
OWNHOME	0.316303	0.357213	0.885474	0.3759
RESPPROB	0.521176	0.354805	1.468906	0.1419
WITNESSFIRE	0.014065	0.308034	0.045662	0.9636
INCOME	4.96E-06	3.93E-06	1.262949	0.2066

Mean dependent var	0.774373	S.D. dependent var	0.418578
S.E. of regression	0.402544	Akaike info criterion	1.017226
Sum squared resid	56.71457	Schwarz criterion	1.114579
Log likelihood	-173.5920	Hannan-Quinn criter.	1.055939
Restr. log likelihood	-191.6837	Avg. log likelihood	-0.483543
LR statistic (8 df)	36.18340	McFadden R-squared	0.094383
Probability(LR stat)	1.63E-05		

Obs with Dep=0	81	Total obs	359
Obs with Dep=1	278		

Mech program without income variable for the CA-FL Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 16:09
Sample(adjusted): 1 471
Included observations: 449
Excluded observations: 22 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.830703	0.810480	1.024952	0.3054
AGE	-0.003370	0.006118	-0.550887	0.5817
EDUC	0.006987	0.049499	0.141158	0.8877
EXPSMOKE	-0.253197	0.255789	-0.989868	0.3222
MECHBID	-0.003317	0.000852	-3.893193	0.0001
OWNHOME	-0.138748	0.247412	-0.560796	0.5749
RESPPROB	0.099148	0.239048	0.414761	0.6783
WITNESSFIRE	-0.149303	0.220175	-0.678112	0.4977

Mean dependent var	0.489978	S.D. dependent var	0.500457
S.E. of regression	0.493482	Akaike info criterion	1.379195
Sum squared resid	107.3943	Schwarz criterion	1.452372
Log likelihood	-301.6294	Hannan-Quinn criter.	1.408040
Restr. log likelihood	-311.1329	Avg. log likelihood	-0.671780
LR statistic (7 df)	19.00700	McFadden R-squared	0.030545
Probability(LR stat)	0.008165		
Obs with Dep=0	229	Total obs	449
Obs with Dep=1	220		

Mech program with income variable for the CA-FL Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 16:09
Sample(adjusted): 1 468
Included observations: 388
Excluded observations: 80 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.871805	0.880878	0.989701	0.3223
AGE	0.005202	0.007009	0.742230	0.4579
EDUC	-0.033775	0.054889	-0.615328	0.5383
EXPSMOKE	-0.360787	0.280666	-1.285468	0.1986
MECHBID	-0.002969	0.000912	-3.256145	0.0011
OWNHOME	-0.250700	0.279335	-0.897491	0.3695
RESPPROB	0.093277	0.258669	0.360603	0.7184
WITNESSFIRE	-0.142861	0.238008	-0.600237	0.5483
INCOME	5.82E-06	2.99E-06	1.943893	0.0519

Mean dependent var	0.512887	S.D. dependent var	0.500479
S.E. of regression	0.494056	Akaike info criterion	1.385488
Sum squared resid	92.51078	Schwarz criterion	1.477367
Log likelihood	-259.7847	Hannan-Quinn criter.	1.421917
Restr. log likelihood	-268.8122	Avg. log likelihood	-0.669548
LR statistic (8 df)	18.05510	McFadden R-squared	0.033583
Probability(LR stat)	0.020817		
Obs with Dep=0	189	Total obs	388
Obs with Dep=1	199		

RX program without income variable for the CA-MT Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 15:52
Sample(adjusted): 1 380
Included observations: 351
Excluded observations: 29 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.198480	0.974786	2.255346	0.0241
AGE	6.32E-05	0.008430	0.007493	0.9940
EXPSMOKE	-0.324604	0.385995	-0.840954	0.4004
EDUC	-0.019125	0.057909	-0.330261	0.7412
RXBID	-0.004637	0.000815	-5.686163	0.0000
OWNHOME	-0.244925	0.332855	-0.735831	0.4618
RESPPROB	0.079736	0.312609	0.255066	0.7987
WITNESSFIRE	0.237231	0.323593	0.733116	0.4635

Mean dependent var	0.700855	S.D. dependent var	0.458537
S.E. of regression	0.439873	Akaike info criterion	1.163693
Sum squared resid	66.36633	Schwarz criterion	1.251688
Log likelihood	-196.2281	Hannan-Quinn criter.	1.198714
Restr. log likelihood	-214.1586	Avg. log likelihood	-0.559054
LR statistic (7 df)	35.86090	McFadden R-squared	0.083725
Probability(LR stat)	7.70E-06		

Obs with Dep=0	105	Total obs	351
Obs with Dep=1	246		

RX program with income variable for the CA-MT Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 15:53
Sample(adjusted): 1 380
Included observations: 338
Excluded observations: 42 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.199163	0.993665	2.213184	0.0269
AGE	0.003045	0.008793	0.346309	0.7291
EXPSMOKE	-0.231979	0.401013	-0.578482	0.5629
EDUC	-0.053829	0.062501	-0.861244	0.3891
RXBID	-0.004712	0.000849	-5.546718	0.0000
OWNHOME	-0.422532	0.356701	-1.184556	0.2362
RESPPROB	0.169751	0.319652	0.531050	0.5954
WITNESSFIRE	0.247700	0.328980	0.752932	0.4515
INCOME	7.25E-06	3.92E-06	1.849793	0.0643

Mean dependent var	0.701183	S.D. dependent var	0.458418
S.E. of regression	0.437512	Akaike info criterion	1.159834
Sum squared resid	62.97616	Schwarz criterion	1.261631
Log likelihood	-187.0120	Hannan-Quinn criter.	1.200405
Restr. log likelihood	-206.1321	Avg. log likelihood	-0.553290
LR statistic (8 df)	38.24015	McFadden R-squared	0.092756
Probability(LR stat)	6.80E-06		

Obs with Dep=0	101	Total obs	338
Obs with Dep=1	237		

Mech program without income variable for the CA-MT Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 16:10
Sample(adjusted): 1 403
Included observations: 391
Excluded observations: 12 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-1.062927	0.811501	-1.309829	0.1903
AGE	0.002970	0.006989	0.424991	0.6708
EDUC	0.109079	0.048067	2.269304	0.0232
EXPSMOKE	-0.706352	0.337549	-2.092587	0.0364
MECHBID	-0.002878	0.000770	-3.739237	0.0002
OWNHOME	-0.274442	0.270608	-1.014167	0.3105
RESPPROB	0.216663	0.266695	0.812400	0.4166
WITNESSFIRE	0.440880	0.293240	1.503479	0.1327

Mean dependent var	0.439898	S.D. dependent var	0.497011
S.E. of regression	0.483907	Akaike info criterion	1.344404
Sum squared resid	89.68570	Schwarz criterion	1.425605
Log likelihood	-254.8310	Hannan-Quinn criter.	1.376590
Restr. log likelihood	-268.1889	Avg. log likelihood	-0.651742
LR statistic (7 df)	26.71578	McFadden R-squared	0.049808
Probability(LR stat)	0.000375		

Obs with Dep=0	219	Total obs	391
Obs with Dep=1	172		

Mech program with income variable for the CA-MT Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 16:10
Sample(adjusted): 1 403
Included observations: 374
Excluded observations: 29 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.563184	0.844906	-0.666564	0.5051
AGE	0.008205	0.007359	1.115026	0.2648
EDUC	0.050728	0.052775	0.961216	0.3364
EXPSMOKE	-0.760571	0.351619	-2.163056	0.0305
MECHBID	-0.003077	0.000804	-3.826940	0.0001
OWNHOME	-0.384163	0.290752	-1.321274	0.1864
RESPPROB	0.204933	0.270895	0.756503	0.4493
WITNESSFIRE	0.324285	0.297003	1.091857	0.2749
INCOME	6.75E-06	3.22E-06	2.098080	0.0359

Mean dependent var	0.451872	S.D. dependent var	0.498345
S.E. of regression	0.482673	Akaike info criterion	1.341670
Sum squared resid	85.03518	Schwarz criterion	1.436104
Log likelihood	-241.8923	Hannan-Quinn criter.	1.379165
Restr. log likelihood	-257.5017	Avg. log likelihood	-0.646771
LR statistic (8 df)	31.21882	McFadden R-squared	0.060619
Probability(LR stat)	0.000128		

Obs with Dep=0	205	Total obs	374
Obs with Dep=1	169		

RX program without income variable for the FL-MT Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 15:55
Sample(adjusted): 1 515
Included observations: 458
Excluded observations: 57 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.622242	0.951887	3.805326	0.0001
AGE	-0.006527	0.007106	-0.918507	0.3584
EXPSMOKE	0.341765	0.359949	0.949480	0.3424
EDUC	-0.146697	0.056223	-2.609205	0.0091
RXBID	-0.005225	0.000821	-6.361067	0.0000
OWNHOME	0.293143	0.296057	0.990157	0.3221
RESPPROB	0.463324	0.276209	1.677437	0.0935
WITNESSFIRE	-0.204094	0.273320	-0.746722	0.4552

Mean dependent var	0.705240	S.D. dependent var	0.456433
S.E. of regression	0.432900	Akaike info criterion	1.129737
Sum squared resid	84.33116	Schwarz criterion	1.201822
Log likelihood	-250.7097	Hannan-Quinn criter.	1.158128
Restr. log likelihood	-277.7123	Avg. log likelihood	-0.547401
LR statistic (7 df)	54.00509	McFadden R-squared	0.097232
Probability(LR stat)	2.35E-09		
Obs with Dep=0	135	Total obs	458
Obs with Dep=1	323		

RX program with income variable for the FL-MT Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 15:55
Sample(adjusted): 10 515
Included observations: 407
Excluded observations: 99 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.835144	1.014158	3.781603	0.0002
AGE	-0.005118	0.007668	-0.667509	0.5044
EXPSMOKE	0.323720	0.403265	0.802748	0.4221
EDUC	-0.172136	0.062086	-2.772545	0.0056
RXBID	-0.004714	0.000867	-5.436544	0.0000
OWNHOME	0.200849	0.322323	0.623129	0.5332
RESPPROB	0.408466	0.291606	1.400744	0.1613
WITNESSFIRE	-0.310757	0.296477	-1.048166	0.2946
INCOME	4.18E-06	4.08E-06	1.025046	0.3053

Mean dependent var	0.710074	S.D. dependent var	0.454286
S.E. of regression	0.434425	Akaike info criterion	1.142132
Sum squared resid	75.11253	Schwarz criterion	1.230779
Log likelihood	-223.4239	Hannan-Quinn criter.	1.177214
Restr. log likelihood	-245.0489	Avg. log likelihood	-0.548953
LR statistic (8 df)	43.24988	McFadden R-squared	0.088247
Probability(LR stat)	7.88E-07		
Obs with Dep=0	118	Total obs	407
Obs with Dep=1	289		

Mech program without income variable for the FL-MT Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 16:11
Sample(adjusted): 1 536
Included observations: 510
Excluded observations: 26 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.983647	0.796248	1.235353	0.2167
AGE	-0.003798	0.005809	-0.653728	0.5133
EDUC	-0.010923	0.046763	-0.233576	0.8153
EXPSMOKE	-0.097919	0.309964	-0.315904	0.7521
MECHBID	-0.004331	0.000814	-5.321692	0.0000
OWNHOME	0.014982	0.247439	0.060550	0.9517
RESPPROB	-0.008944	0.224980	-0.039753	0.9683
WITNESSFIRE	-0.356932	0.218238	-1.635520	0.1019

Mean dependent var	0.435294	S.D. dependent var	0.496282
S.E. of regression	0.481321	Akaike info criterion	1.328746
Sum squared resid	116.2982	Schwarz criterion	1.395168
Log likelihood	-330.8302	Hannan-Quinn criter.	1.354788
Restr. log likelihood	-349.2225	Avg. log likelihood	-0.648687
LR statistic (7 df)	36.78446	McFadden R-squared	0.052666
Probability(LR stat)	5.15E-06		
Obs with Dep=0	288	Total obs	510
Obs with Dep=1	222		

Mech program with income variable for the FL-MT

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 16:11
Sample(adjusted): 1 536
Included observations: 450
Excluded observations: 86 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.310699	0.871924	1.503226	0.1328
AGE	-0.001922	0.006356	-0.302389	0.7624
EDUC	-0.066616	0.053030	-1.256201	0.2090
EXPSMOKE	-0.099926	0.343036	-0.291299	0.7708
MECHBID	-0.003905	0.000851	-4.591846	0.0000
OWNHOME	-0.064650	0.269493	-0.239896	0.8104
RESPPROB	-0.008497	0.240198	-0.035374	0.9718
WITNESSFIRE	-0.342465	0.235225	-1.455907	0.1454
INCOME	8.75E-06	3.66E-06	2.392797	0.0167

Mean dependent var	0.444444	S.D. dependent var	0.497457
S.E. of regression	0.483062	Akaike info criterion	1.339550
Sum squared resid	102.9067	Schwarz criterion	1.421735
Log likelihood	-292.3988	Hannan-Quinn criter.	1.371943
Restr. log likelihood	-309.1327	Avg. log likelihood	-0.649775
LR statistic (8 df)	33.46773	McFadden R-squared	0.054132
Probability(LR stat)	5.07E-05		
Obs with Dep=0	250	Total obs	450
Obs with Dep=1	200		

RX program without income variable for the Hispanics

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 15:57
Sample(adjusted): 1 581
Included observations: 505
Excluded observations: 76 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	4.469499	0.802226	5.571373	0.0000
AGE	-0.007836	0.007612	-1.029315	0.3033
EXPSMOKE	0.259531	0.269591	0.962686	0.3357
EDUC	-0.172635	0.053557	-3.223378	0.0013
RXBID	-0.002900	0.000828	-3.501962	0.0005
OWNHOME	-0.360231	0.251809	-1.430573	0.1526
RESPPROB	0.027069	0.306530	0.088306	0.9296
WITNESSFIRE	0.075114	0.282252	0.266124	0.7901

Mean dependent var	0.792079	S.D. dependent var	0.406222
S.E. of regression	0.398506	Akaike info criterion	1.000955
Sum squared resid	78.92706	Schwarz criterion	1.067878
Log likelihood	-244.7410	Hannan-Quinn criter.	1.027204
Restr. log likelihood	-258.1504	Avg. log likelihood	-0.484636
LR statistic (7 df)	26.81867	McFadden R-squared	0.051944
Probability(LR stat)	0.000359		
Obs with Dep=0	105	Total obs	505
Obs with Dep=1	400		

RX program with income variable for the Hispanics

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 15:58
Sample(adjusted): 1 540
Included observations: 458
Excluded observations: 82 after adjusting endpoints
Convergence achieved after 6 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	4.599500	0.821990	5.595569	0.0000
AGE	-0.007892	0.008059	-0.979334	0.3274
EXPSMOKE	0.158406	0.276560	0.572771	0.5668
EDUC	-0.206180	0.056685	-3.637303	0.0003
RXBID	-0.002950	0.000856	-3.446756	0.0006
OWNHOME	-0.475632	0.265389	-1.792210	0.0731
RESPPROB	0.028687	0.314251	0.091286	0.9273
WITNESSFIRE	0.140201	0.292438	0.479422	0.6316
INCOME	9.57E-06	5.70E-06	1.677314	0.0935

Mean dependent var	0.775109	S.D. dependent var	0.417967
S.E. of regression	0.408246	Akaike info criterion	1.039870
Sum squared resid	74.83241	Schwarz criterion	1.120966
Log likelihood	-229.1303	Hannan-Quinn criter.	1.071810
Restr. log likelihood	-244.1272	Avg. log likelihood	-0.500284
LR statistic (8 df)	29.99380	McFadden R-squared	0.061431
Probability(LR stat)	0.000212		
Obs with Dep=0	103	Total obs	458
Obs with Dep=1	355		

Mech program without income variable for the Hispanics

Dependent Variable: VOTEMECHPRGM
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 16:13
Sample(adjusted): 1 557
Included observations: 531
Excluded observations: 26 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.467295	0.659100	5.260648	0.0000
AGE	0.002754	0.006492	0.424218	0.6714
EDUC	-0.209513	0.045147	-4.640709	0.0000
EXPSMOKE	0.070275	0.221129	0.317803	0.7506
MECHBID	-0.001326	0.000687	-1.932050	0.0534
OWNHOME	-0.139980	0.204425	-0.684749	0.4935
RESPPROB	-0.122693	0.247464	-0.495801	0.6200
WITNESSFIRE	0.114684	0.231029	0.496404	0.6196

Mean dependent var	0.640301	S.D. dependent var	0.480365
S.E. of regression	0.470730	Akaike info criterion	1.281835
Sum squared resid	115.8899	Schwarz criterion	1.346239
Log likelihood	-332.3273	Hannan-Quinn criter.	1.307042
Restr. log likelihood	-346.8729	Avg. log likelihood	-0.625852
LR statistic (7 df)	29.09119	McFadden R-squared	0.041934
Probability(LR stat)	0.000139		
Obs with Dep=0	191	Total obs	531
Obs with Dep=1	340		

Mech program with income variable for the Hispanics

Dependent Variable: VOTEMECHPRGM
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 16:13
Sample(adjusted): 1 523
Included observations: 487
Excluded observations: 36 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.518160	0.675131	5.211081	0.0000
AGE	0.001822	0.006935	0.262791	0.7927
EDUC	-0.218267	0.047373	-4.607449	0.0000
EXPSMOKE	-0.052582	0.229126	-0.229489	0.8185
MECHBID	-0.001522	0.000711	-2.141870	0.0322
OWNHOME	-0.281206	0.217728	-1.291549	0.1965
RESPPROB	-0.205591	0.257816	-0.797433	0.4252
WITNESSFIRE	0.171211	0.241319	0.709481	0.4780
INCOME	4.76E-06	4.38E-06	1.088337	0.2764

Mean dependent var	0.616016	S.D. dependent var	0.486854
S.E. of regression	0.475631	Akaike info criterion	1.304098
Sum squared resid	108.1353	Schwarz criterion	1.381499
Log likelihood	-308.5479	Hannan-Quinn criter.	1.334504
Restr. log likelihood	-324.3326	Avg. log likelihood	-0.633569
LR statistic (8 df)	31.56934	McFadden R-squared	0.048668
Probability(LR stat)	0.000111		
Obs with Dep=0	187	Total obs	487
Obs with Dep=1	300		

APPENDIX 11: **Regressions on significant independent variables** (Reduced form and Protest responses excluded)

RX program for the CA Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/13/04 Time: 00:07
Sample(adjusted): 1 155
Included observations: 154
Excluded observations: 1 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.258908	0.349301	6.466939	0.0000
RXBID	-0.005656	0.001418	-3.989075	0.0001

Mean dependent var	0.779221	S.D. dependent var	0.416125
S.E. of regression	0.394348	Akaike info criterion	0.971365
Sum squared resid	23.63761	Schwarz criterion	1.010806
Log likelihood	-72.79510	Hannan-Quinn criter.	0.987386
Restr. log likelihood	-81.29543	Avg. log likelihood	-0.472695
LR statistic (1 df)	17.00067	McFadden R-squared	0.104561
Probability(LR stat)	3.74E-05		

Obs with Dep=0	34	Total obs	154
Obs with Dep=1	120		

Mech program for the CA Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/13/04 Time: 00:10
Sample(adjusted): 1 173
Included observations: 157
Excluded observations: 16 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.050411	0.707398	-0.071263	0.9432
MECHBID	-0.002556	0.001230	-2.077504	0.0378
AGE	0.015921	0.010989	1.448731	0.1474
EXPSMOKE	-0.581146	0.366328	-1.586407	0.1126
INCOME	3.48E-06	3.62E-06	0.960401	0.3369

Mean dependent var	0.541401	S.D. dependent var	0.499877
S.E. of regression	0.492215	Akaike info criterion	1.385979
Sum squared resid	36.82584	Schwarz criterion	1.483311
Log likelihood	-103.7993	Hannan-Quinn criter.	1.425509
Restr. log likelihood	-108.2853	Avg. log likelihood	-0.661142
LR statistic (4 df)	8.971923	McFadden R-squared	0.041427
Probability(LR stat)	0.061805		

Obs with Dep=0	72	Total obs	157
Obs with Dep=1	85		

RX program for the FL Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/13/04 Time: 00:15
Sample(adjusted): 1 292
Included observations: 260
Excluded observations: 32 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	4.353172	1.281016	3.398218	0.0007
RXBID	-0.006965	0.001459	-4.773026	0.0000
EDU	-0.210963	0.082137	-2.568442	0.0102
OWNHOME	0.726814	0.373192	1.947560	0.0515
RESPPROB	0.848499	0.405978	2.090014	0.0366

Mean dependent var	0.750000	S.D. dependent var	0.433848
S.E. of regression	0.408942	Akaike info criterion	1.030760
Sum squared resid	42.64458	Schwarz criterion	1.099235
Log likelihood	-128.9988	Hannan-Quinn criter.	1.058288
Restr. log likelihood	-146.2071	Avg. log likelihood	-0.496149
LR statistic (4 df)	34.41663	McFadden R-squared	0.117698
Probability(LR stat)	6.12E-07		
Obs with Dep=0	65	Total obs	260
Obs with Dep=1	195		

Mech program for the FL Whites

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/13/04 Time: 00:17
Sample(adjusted): 1 294
Included observations: 239
Excluded observations: 55 after adjusting endpoints
Convergence achieved after 8 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.958628	1.192627	2.480765	0.0131
MECHBID	-0.003989	0.001446	-2.758247	0.0058
EDU	-0.174620	0.080284	-2.175025	0.0296
INCOME	7.96E-06	4.44E-06	1.791021	0.0733
WITNESSFIRE	-0.578897	0.279288	-2.072756	0.0382

Mean dependent var	0.493724	S.D. dependent var	0.501010
S.E. of regression	0.484712	Akaike info criterion	1.347731
Sum squared resid	54.97735	Schwarz criterion	1.420460
Log likelihood	-156.0538	Hannan-Quinn criter.	1.377039
Restr. log likelihood	-165.6433	Avg. log likelihood	-0.652945
LR statistic (4 df)	19.17902	McFadden R-squared	0.057893
Probability(LR stat)	0.000725		
Obs with Dep=0	121	Total obs	239
Obs with Dep=1	118		

RX program for the MT Whites

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/13/04 Time: 00:19
Sample(adjusted): 1 202
Included observations: 202 after adjusting endpoints
Convergence achieved after 3 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.283829	0.234504	5.474667	0.0000
RXBID	-0.004034	0.000995	-4.056234	0.0000

Mean dependent var	0.643564	S.D. dependent var	0.480136
S.E. of regression	0.460844	Akaike info criterion	1.236219
Sum squared resid	42.47551	Schwarz criterion	1.268974
Log likelihood	-122.8581	Hannan-Quinn criter.	1.249471
Restr. log likelihood	-131.5706	Avg. log likelihood	-0.608208
LR statistic (1 df)	17.42512	McFadden R-squared	0.066220
Probability(LR stat)	2.99E-05		

Obs with Dep=0	72	Total obs	202
Obs with Dep=1	130		

Mech program for the MT Whites

Dependent Variable: VOTEMECPGM
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/13/04 Time: 00:21
Sample(adjusted): 1 229
Included observations: 221
Excluded observations: 8 after adjusting endpoints
Convergence achieved after 6 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.220056	0.304221	-0.723343	0.4695
MECHBID	-0.003701	0.001078	-3.432797	0.0006
INCOME	8.38E-06	5.14E-06	1.629510	0.1032

Mean dependent var	0.393665	S.D. dependent var	0.489671
S.E. of regression	0.473960	Akaike info criterion	1.296807
Sum squared resid	48.97107	Schwarz criterion	1.342936
Log likelihood	-140.2971	Hannan-Quinn criter.	1.315433
Restr. log likelihood	-148.1494	Avg. log likelihood	-0.634829
LR statistic (2 df)	15.70454	McFadden R-squared	0.053002
Probability(LR stat)	0.000389		

Obs with Dep=0	134	Total obs	221
Obs with Dep=1	87		

RX program or the CA Hispanics

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/13/04 Time: 00:23
Sample(adjusted): 1 301
Included observations: 269
Excluded observations: 32 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	4.044987	0.999256	4.047998	0.0001
RXBID	-0.002326	0.001118	-2.080471	0.0375
EDUC	-0.151679	0.075301	-2.014295	0.0440

Mean dependent var	0.855019	S.D. dependent var	0.352738
S.E. of regression	0.348132	Akaike info criterion	0.820089
Sum squared resid	32.23802	Schwarz criterion	0.860179
Log likelihood	-107.3020	Hannan-Quinn criter.	0.836189
Restr. log likelihood	-111.3402	Avg. log likelihood	-0.398892
LR statistic (2 df)	8.076415	McFadden R-squared	0.036269
Probability(LR stat)	0.017629		

Obs with Dep=0	39	Total obs	269
Obs with Dep=1	230		

Mech program the CA Hispanics

RX program or the FL Hispanics

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/13/04 Time: 00:29
Sample(adjusted): 1 239
Included observations: 214
Excluded observations: 25 after adjusting endpoints
Convergence achieved after 6 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.503512	0.346841	1.451708	0.1466
RXBID	-0.003895	0.001322	-2.946244	0.0032
INCOME	2.26E-05	9.00E-06	2.507560	0.0122

Mean dependent var	0.682243	S.D. dependent var	0.466696
S.E. of regression	0.453238	Akaike info criterion	1.206025
Sum squared resid	43.34470	Schwarz criterion	1.253212
Log likelihood	-126.0447	Hannan-Quinn criter.	1.225093
Restr. log likelihood	-133.7858	Avg. log likelihood	-0.588994
LR statistic (2 df)	15.48220	McFadden R-squared	0.057862
Probability(LR stat)	0.000435		

Obs with Dep=0	68	Total obs	214
Obs with Dep=1	146		

Mech program the FL Hispanics

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/13/04 Time: 00:27
Sample(adjusted): 1 254
Included observations: 248
Excluded observations: 6 after adjusting endpoints
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.615561	1.194771	3.026155	0.0025
MECHBID	-0.002842	0.001140	-2.493458	0.0127
EDU	-0.202880	0.081387	-2.492769	0.0127

Mean dependent var	0.584677	S.D. dependent var	0.493774
S.E. of regression	0.483746	Akaike info criterion	1.333755
Sum squared resid	57.33243	Schwarz criterion	1.376256
Log likelihood	-162.3856	Hannan-Quinn criter.	1.350864
Restr. log likelihood	-168.3269	Avg. log likelihood	-0.654781
LR statistic (2 df)	11.88245	McFadden R-squared	0.035296
Probability(LR stat)	0.002629		

Obs with Dep=0	103	Total obs	248
Obs with Dep=1	145		

Appendix 12: **Regressions of three state pooled data for scope test**

RX program for the Whites with all variables

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/10/04 Time: 20:51
Sample(adjusted): 2 785
Included observations: 583
Excluded observations: 201 after adjusting endpoints
Convergence achieved after 8 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.463822	0.796883	1.836935	0.0662
RXBID	-0.004491	0.000706	-6.363373	0.0000
ACREREDUCTION	1.17E-05	4.86E-06	2.401563	0.0163
AGE	-0.003228	0.006378	-0.506138	0.6128
EDUC	-0.047168	0.047560	-0.991759	0.3213
EXPSMOKE	0.024680	0.297957	0.082830	0.9340
INCOME	2.81E-06	3.06E-06	0.918712	0.3582
OWNHOME	0.022865	0.264094	0.086578	0.9310
RESPPROB	0.268174	0.234745	1.142409	0.2533
WITNESSFIRE	-0.070072	0.231575	-0.302591	0.7622

Mean dependent var	0.689537	S.D. dependent var	0.463081
S.E. of regression	0.445540	Akaike info criterion	1.182178
Sum squared resid	113.7439	Schwarz criterion	1.257104
Log likelihood	-334.6048	Hannan-Quinn criter.	1.211382
Restr. log likelihood	-361.1514	Avg. log likelihood	-0.57393
LR statistic (9 df)	53.09334	McFadden R-squared	0.073506
Probability(LR stat)	2.81E-08		

Obs with Dep=0	181	Total obs	583
Obs with Dep=1	402		

RX program for the Whites with uncontrolled variables only

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/10/04 Time: 20:54
Sample(adjusted): 2 787
Included observations: 658
Excluded observations: 128 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.789900	0.259460	3.044398	0.0023
RXBID	-0.004538	0.000656	-6.913734	0.0000
ACREREDUCTION	1.17E-05	4.30E-06	2.718185	0.0066

Mean dependent var	0.682371	S.D. dependent var	0.465909
S.E. of regression	0.445947	Akaike info criterion	1.171368
Sum squared resid	130.2590	Schwarz criterion	1.191835
Log likelihood	-382.3799	Hannan-Quinn criter.	1.179302
Restr. log likelihood	-411.2957	Avg. log likelihood	-0.581124
LR statistic (2 df)	57.83159	McFadden R-squared	0.070304
Probability(LR stat)	2.77E-13		

Obs with Dep=0	209	Total obs	658
Obs with Dep=1	449		

Mech program for the Whites with all variables

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 11:17
Sample(adjusted): 1 785
Included observations: 673
Excluded observations: 112 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.020766	0.690346	0.030081	0.9760
ACREREDUCTION	6.37E-06	4.10E-06	1.554443	0.1201
MECHBID	-0.003017	0.000670	-4.499948	0.0000
AGE	0.003950	0.005402	0.731130	0.4647
EDUC	-0.011696	0.040558	-0.288369	0.7731
OWNHOME	-0.213931	0.221783	-0.964598	0.3347
RESPPROB	0.109500	0.198022	0.552970	0.5803
INCOME	5.40E-06	2.54E-06	2.129980	0.0332
EXPSMOKE	-0.369802	0.254356	-1.453874	0.1460
WITNESSFIRE	-0.192145	0.196604	-0.977319	0.3284

Mean dependent var	0.421991	S.D. dependent var	0.494244
S.E. of regression	0.482644	Akaike info criterion	1.331924
Sum squared resid	154.4426	Schwarz criterion	1.398964
Log likelihood	-438.1926	Hannan-Quinn criter.	1.357886
Restr. log likelihood	-458.2636	Avg. log likelihood	-0.651103
LR statistic (9 df)	40.14194	McFadden R-squared	0.043798
Probability(LR stat)	7.16E-06		
Obs with Dep=0	389	Total obs	673
Obs with Dep=1	284		

Mech program for the Whites with uncontrolled variables only

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 11:15
Sample(adjusted): 1 787
Included observations: 764
Excluded observations: 23 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.481902	0.222757	-2.163354	0.0305
ACREREDUCTION	1.05E-05	3.60E-06	2.902446	0.0037
MECHBID	-0.003107	0.000626	-4.962041	0.0000

Mean dependent var	0.416230	S.D. dependent var	0.493256
S.E. of regression	0.482895	Akaike info criterion	1.320352
Sum squared resid	177.4560	Schwarz criterion	1.338566
Log likelihood	-501.3744	Hannan-Quinn criter.	1.327364
Restr. log likelihood	-518.7912	Avg. log likelihood	-0.656249
LR statistic (2 df)	34.83352	McFadden R-squared	0.033572
Probability(LR stat)	2.73E-08		
Obs with Dep=0	446	Total obs	764
Obs with Dep=1	318		

RX program for the Hispanics with all variables

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 22:38
Sample(adjusted): 1 588
Included observations: 478
Excluded observations: 110 after adjusting endpoints
Convergence achieved after 8 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.493174	1.132742	1.318194	0.1874
ACREREDUCTION	2.27E-05	6.68E-06	3.401300	0.0007
RXBID	-0.002716	0.000832	-3.262509	0.0011
AGE	-0.006857	0.007686	-0.892104	0.3723
EDUC	-0.088129	0.059063	-1.492117	0.1357
EXPSMOKE	0.252723	0.263375	0.959553	0.3373
INCOME	-4.28E-06	4.64E-06	-0.922482	0.3563
OWNHOME	-0.238847	0.258048	-0.925590	0.3547
RESPPROB	-0.095309	0.290631	-0.327938	0.7430
WITNESSFIRE	0.165943	0.273914	0.605821	0.5446

Mean dependent var	0.742678	S.D. dependent var	0.437616
S.E. of regression	0.422228	Akaike info criterion	1.093457
Sum squared resid	83.43343	Schwarz criterion	1.180687
Log likelihood	-251.3362	Hannan-Quinn criter.	1.127751
Restr. log likelihood	-272.5734	Avg. log likelihood	-0.525808
LR statistic (9 df)	42.47439	McFadden R-squared	0.077914
Probability(LR stat)	2.69E-06		

Obs with Dep=0	123	Total obs	478
Obs with Dep=1	355		

RX program for the Hispanics with uncontrolled variables only

Dependent Variable: VOTERXPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 22:39
Sample(adjusted): 1 648
Included observations: 555
Excluded observations: 93 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.222987	0.356799	-0.624966	0.5320
ACREREDUCTION	2.50E-05	5.32E-06	4.697981	0.0000
RXBID	-0.002470	0.000775	-3.186792	0.0014

Mean dependent var	0.754955	S.D. dependent var	0.430502
S.E. of regression	0.419657	Akaike info criterion	1.071778
Sum squared resid	97.21379	Schwarz criterion	1.095123
Log likelihood	-294.4183	Hannan-Quinn criter.	1.080897
Restr. log likelihood	-309.0383	Avg. log likelihood	-0.530483
LR statistic (2 df)	29.24012	McFadden R-squared	0.047308
Probability(LR stat)	4.47E-07		

Obs with Dep=0	136	Total obs	555
Obs with Dep=1	419		

Mech program for the Hispanics with all variables

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 22:57
Sample(adjusted): 1 588
Included observations: 516
Excluded observations: 72 after adjusting endpoints
Convergence achieved after 8 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.787205	0.975346	1.832380	0.0669
ACREREDUCTION	1.47E-05	5.61E-06	2.625017	0.0087
MECHBID	-0.001152	0.000697	-1.653135	0.0983
EDUC	-0.176606	0.050899	-3.469715	0.0005
AGE	-0.000218	0.006654	-0.032709	0.9739
INCOME	1.11E-06	3.98E-06	0.279333	0.7800
EXPSMOKE	0.081885	0.220178	0.371903	0.7100
OWNHOME	-0.098988	0.216250	-0.457745	0.6471
RESPPROB	-0.234385	0.248434	-0.943452	0.3454
WITNESSFIRE	0.135477	0.229867	0.589375	0.5556

Mean dependent var	0.581395	S.D. dependent var	0.493809
S.E. of regression	0.478352	Akaike info criterion	1.316281
Sum squared resid	115.7833	Schwarz criterion	1.398570
Log likelihood	-329.6005	Hannan-Quinn criter.	1.348527
Restr. log likelihood	-350.7962	Avg. log likelihood	-0.638761
LR statistic (9 df)	42.39143	McFadden R-squared	0.060422
Probability(LR stat)	2.79E-06		
Obs with Dep=0	216	Total obs	516
Obs with Dep=1	300		

Mech program for the Hispanics with uncontrolled variables only

Dependent Variable: VOTEMECHPR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/12/04 Time: 23:02
Sample(adjusted): 1 653
Included observations: 601
Excluded observations: 52 after adjusting endpoints
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.957385	0.310247	-3.085878	0.0020
ACREREDUCTION	2.03E-05	4.32E-06	4.693578	0.0000
MECHBID	-0.000649	0.000639	-1.015753	0.3097

Mean dependent var	0.587354	S.D. dependent var	0.492720
S.E. of regression	0.484136	Akaike info criterion	1.327750
Sum squared resid	140.1640	Schwarz criterion	1.349706
Log likelihood	-395.9888	Hannan-Quinn criter.	1.336296
Restr. log likelihood	-407.3620	Avg. log likelihood	-0.658883
LR statistic (2 df)	22.74632	McFadden R-squared	0.027919
Probability(LR stat)	1.15E-05		
Obs with Dep=0	248	Total obs	601
Obs with Dep=1	353		

Appendix 13: **Confidence intervals of Willingness to Pay**

Confidence interval for White-CA-RX

```
C:\DOCUME~1\HUNGTR~1\MYDOCU~1\Gauss\GAUSS.EXE
**********************************************
CONFIDENCE INTERVALS FOR DICHOTOMOUS CHOICE CV
**********************************************
CI for White-CA-RX

Grand constant and price coefficients
  1.8135 -0.0046110

repetitions used to form CI's =    4000.0

99 ci      295.24    1335.4

95 ci      314.75    811.74

90 ci      327.94    694.42

>>

Alt-H for help                    L=17   C=3   Path=C:\DOCUME~1\HUNGTR~1\MYDOCU~
```

Confidence interval for White-FL-RX

```
C:\DOCUME~1\HUNGTR~1\MYDOCU~1\Gauss\GAUSS.EXE
**********************************************
CONFIDENCE INTERVALS FOR DICHOTOMOUS CHOICE CV
**********************************************
CI for White-FL-RX

Grand constant and price coefficients
  1.6321 -0.0059380

repetitions used to form CI's =    4000.0

99 ci      223.02    585.81

95 ci      238.17    460.74

90 ci      245.23    429.07

>> _

Alt-H for help                    L=17   C=3   Path=C:\DOCUME~1\HUNGTR~1\MYDOCU~
```

Confidence interval for White-FL-Mech

```
C:\DOCUME~1\HUNGTR~1\MYDOCU~1\Gauss\GAUSS.EXE
**********************************************
CONFIDENCE INTERVALS FOR DICHOTOMOUS CHOICE CV
**********************************************
CI for White-FL-Mech

Grand constant and price coefficients
 0.23540 -0.0039440

repetitions used to form CI's =    4000.0

99 ci      128.37    1307.7

95 ci      140.74    535.01

90 ci      146.25    409.19

>>

Alt-H for help                    L=17   C=3   Path=C:\DOCUME~1\HUNGTR~1\MYDOCU~
```

Confidence interval for White-MT-RX

```
C:\DOCUME~1\HUNGTR~1\MYDOCU~1\Gauss\GAUSS.EXE
**********************************************
CONFIDENCE INTERVALS FOR DICHOTOMOUS CHOICE CV
**********************************************
CI for White-MT-RX

Grand constant and price coefficients
 0.95657 -0.0035020

repetitions used to form CI's =    4000.0

99 ci      248.95    952.67

95 ci      269.24    655.60

90 ci      280.50    568.42

>> _

Alt-H for help                    L=17   C=3   Path=C:\DOCUME~1\HUNGTR~1\MYDOCU~
```

Confidence interval for White-MT-Mech

```
C:\DOCUME~1\HUNGTR~1\MYDOCU~1\Gauss\GAUSS.EXE
**********************************************
CONFIDENCE INTERVALS FOR DICHOTOMOUS CHOICE CV
**********************************************
CI for White-MT-Mech

Grand constant and price coefficients
-0.16990 -0.0033290

repetitions used to form CI's =   4000.0

99 ci      120.69    696.23

95 ci      131.17    377.23

90 ci      137.78    317.33

>>

Alt-H for help                     L=17   C=3   Path=C:\DOCUME~1\HUNGTR~1\MYDOCU~
```

Confidence interval for Hisp-CA-RX

```
C:\DOCUME~1\HUNGTR~1\MYDOCU~1\Gauss\GAUSS.EXE
**********************************************
CONFIDENCE INTERVALS FOR DICHOTOMOUS CHOICE CV
**********************************************
CI for Hisp-CA-RX

Grand constant and price coefficients
  1.9183 -0.0016190

repetitions used to form CI's =   4000.0

99 ci      555.91    87302.

95 ci      622.32    17822.

90 ci      674.23    9870.1

>> _

Alt-H for help                     L=17   C=3   Path=C:\DOCUME~1\HUNGTR~1\MYDOCU~
```

Confidence interval for Hisp-FL-RX

```
C:\DOCUME~1\HUNGTR~1\MYDOCU~1\Gauss\GAUSS.EXE
**********************************************
CONFIDENCE INTERVALS FOR DICHOTOMOUS CHOICE CV
**********************************************
CI for Hisp-FL-RX

Grand constant and price coefficients
  1.1508 -0.0034670

repetitions used to form CI's =   4000.0

99 ci      264.94    1997.1

95 ci      283.93    1035.0

90 ci      297.06    795.44

>>

Alt-H for help                     L=17   C=3   Path=C:\DOCUME~1\HUNGTR~1\MYDOCU~
```

Confidence interval for Hisp-FL-Mech

```
C:\DOCUME~1\HUNGTR~1\MYDOCU~1\Gauss\GAUSS.EXE
**********************************************
CONFIDENCE INTERVALS FOR DICHOTOMOUS CHOICE CV
**********************************************
CI for Hisp-FL-Mech

Grand constant and price coefficients
 0.24090 -0.0019760

repetitions used to form CI's =   4000.0

99 ci      209.75    18052.

95 ci      232.97    3589.2

90 ci      249.47    2024.7

>> _

Alt-H for help                     L=17   C=3   Path=C:\DOCUME~1\HUNGTR~1\MYDOCU~
```

APPEDIX 14: **Regressions with labor and money contribution dependent variables for Vietnam study**

Labor contribution

Dependent Variable: LABORC
Method: Least Squares
Date: 05/05/04 Time: 20:11
Sample(adjusted): 1 70
Included observations: 63
Excluded observations: 7 after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.851287	2.658964	-1.072330	0.2882
EDUCATION	0.414096	0.141734	2.921641	0.0050
FARMER	3.038619	1.084853	2.800950	0.0070
FIREINFLUENCE	0.554229	0.842204	0.658070	0.5132
FIRESEE	0.383791	1.322617	0.290176	0.7728
NUMBERPEOPLE	0.238741	0.367567	0.649516	0.5187
YEARLIVE	0.031065	0.031038	1.000868	0.3212

R-squared	0.197724	Mean dependent var	4.817460
Adjusted R-squared	0.111766	S.D. dependent var	2.965258
S.E. of regression	2.794643	Akaike info criterion	4.997725
Sum squared resid	437.3616	Schwarz criterion	5.235851
Log likelihood	-150.4283	F-statistic	2.300232
Durbin-Watson stat	1.767873	Prob(F-statistic)	0.046934

Money contribution

Dependent Variable: MONEYC
Method: ML - Censored Normal (TOBIT) (Quadratic hill climbing)
Date: 05/05/04 Time: 20:20
Sample(adjusted): 1 70
Included observations: 63
Excluded observations: 7 after adjusting endpoints
Left censoring (value) at zero
Convergence achieved after 9 iterations
Covariance matrix computed using second derivatives

	Coefficient	Std. Error	z-Statistic	Prob.
C	-183525.0	153106.2	-1.198678	0.2307
FIRESEE	-80415.26	72079.21	-1.115651	0.2646
FIREINFLUENCE	24767.05	50456.55	0.490859	0.6235
NUMBERPEOPLE	4469.003	22509.20	0.198541	0.8426
YEARLIVE	1893.437	1691.838	1.119160	0.2631
FARMER	-102917.2	74738.27	-1.377034	0.1685
EDUCATION	10131.73	8635.671	1.173242	0.2407
Error Distribution				
SCALE:C(8)	104725.2	24974.86	4.193226	0.0000

R-squared	0.227585	Mean dependent var	9722.222
Adjusted R-squared	0.129278	S.D. dependent var	40563.35
S.E. of regression	37850.67	Akaike info criterion	5.171195
Sum squared resid	7.88E+10	Schwarz criterion	5.443339
Log likelihood	-154.8926	Hannan-Quinn criter.	5.278230
Avg. log likelihood	-2.458613		
Left censored obs	52	Right censored obs	0
Uncensored obs	11	Total obs	63