A Comparison of Methodologies for Valuing Decreased Health Effects from Wildfire Smoke

Leslie Richardson[a], John Loomis[b], Patricia A. Champ[c]

[a]Department of Agricultural and Resource Economics, Colorado State University, Fort Collins, CO 80523-1172, USA, leslier@rams.colostate.edu
[b]Department of Agricultural and Resource Economics, Colorado State University, Fort Collins, CO 80523-1172, USA
[c]Rocky Mountain Research Station, USDA Forest Service, 2150 Centre Avenue, Suite 350, Fort Collins, CO 80526, USA

Selected Paper prepared for presentation at the Agricultural & Applied Economics Association 2010 AAEA, CAES, & WAEA Joint Annual Meeting, Denver, Colorado, July 25-27, 2010

It is widely understood that certain air pollutants can negatively affect human health and this represents a real cost to society. Looking forward, if policy-makers are to accurately evaluate policies to reduce air pollutants to estimate whether such policies result in a net benefit to society, the full economic cost of the damages from the pollutant should be included in such a calculation. This includes the cost of damages to human health that results from exposure to the pollutant. The question then becomes how to accurately monetize the economic cost of these health damages, also known as morbidity effects.

In the past, economists relied on a simple cost of illness, or damage function, approach to estimate the economic cost of health effects from various air pollutants. A cost of illness (COI) approach sums resource and opportunity costs of being sick to arrive at a final cost of damages to human health from a particular pollutant. These include individual's expenditures on medical care and medications, the opportunity cost of time spent in obtaining medical care, and lost wages from not being able to work. The damage function approach uses empirical data to estimate how various levels of a particular pollutant will affect human health outcomes, and then connects these health outcomes with associated economic costs to arrive at a final cost of illness.

However, it has been found over the years that these approaches will largely underestimate the true economic cost of health damages from exposure to a pollutant. According to Freeman (2003), an air pollutant that affects human health impacts well-being in four ways: incurred medical expenses, lost wages, expenditures on activities taken to avoid the health effects, and the disutility associated with symptoms or lost leisure. The cost of illness, or damage function, approach ignores these last two components. Therefore, the theoretically correct measure of the cost of health damages from exposure to a pollutant is the individual willingness-to-pay (WTP) to avoid this damage (Freeman 2003). For this reason, researchers have turned to the contingent valuation method (CVM), as well as the averting behavior method (ABM), in an effort to monetize the true cost of damages to human health from various air pollutants. Therefore, there are three common approaches to value reductions in morbidity from exposure to pollutants: the cost of illness approach, the contingent valuation method and the averting behavior method. But for reasons mentioned above, the cost of illness approach underestimates the true economic costs.

Over the years, various studies have used one or more of these three approaches to value reductions in air pollutants or the health effects associated with them. Loehman et al. (1979), Loehman and De (1982), Berger et al. (1985), Dickie et al. (1987), Alberini et al. (1997), and Alberini and Krupnick (1998) use the contingent valuation method to value reductions in symptoms from various air pollutants. In addition, Alberini and Krupnick (2000) compare cost of illness estimates with WTP estimates from a contingent valuation survey to value the benefits of improved air quality in Taiwan. They find that WTP estimates exceed COI estimates by a factor of 1.61 to 2.26.

In addition, there have been a few studies using the averting behavior method to obtain WTP values for a reduction in exposure to an air pollutant or the symptoms that result from it. These include Cropper (1981), Gerking and Stanley (1986), Joyce et al. (1989), Dickie and Gerking (1991), Bresnahan, Dickie, and Gerking (1997) and Dickie (2005). Mansfield et al. (2006) combine stated preference data and averting behavior data to estimate parent's WTP for a decrease in children's exposure to ozone.

While the contingent valuation and averting behavior methods have been repeatedly used to estimate the economic cost of health effects from exposure to various air pollutants, they have never been applied to the health effects resulting from wildfire smoke. The smoke released by wildfires is made up of a number of pollutants, the most problematic of which is particulate matter (PM), a complex mixture of extremely small particles and liquid droplets. According to the U.S. Environmental Protection Agency (2008), exposure to particulate matter has been linked to numerous health effects, including increased respiratory symptoms, decreased lung function, aggravated asthma, development of chronic bronchitis, irregular heartbeat and nonfatal heart attacks. Children, the elderly, and people with preexisting heart and lung conditions are the most likely to be affected. However, the costs imposed on society as a result of these potential health effects are often unknown or underestimated. Valuing the cost of health damages from particulate matter is increasingly relevant given the fact that wildfire seasons are becoming longer and more intense in many parts of the world. Various fire management policies, such as prescribed burns, are quite costly, and in determining if they have net benefits compared to the status quo, the full damages of each wildfire should be monetized, and this includes the full economic costs imposed on individuals as a result of morbidity from wildfire smoke.

Unfortunately, there is a lack of literature available to policy makers to guide them in their quest to obtain these costs. While some studies have estimated the morbidity effects that result from wildfire smoke (Anaman 2001; Mott et al. 2005; Sutherland et al. 2005), few attempt to monetize the economic cost of these impacts. The studies that have tend to use a cost of illness approach. Many rely on previously obtained dose-response or damage functions that relate various levels of particulate matter to expected health outcomes. They then connect these estimates with previously obtained costs associated with these health effects to arrive at a final cost of illness resulting from wildfire smoke (Ruitenbeek 1999; Martin et al. 2007; Rittmaster et al. 2006). This can be problematic as many of the dose response functions used have looked at the effect of low to moderate levels of particulate matter on human health, coming from continuous exposure to industrial sources of pollution. This exposure can be quite different from that of wildfire smoke, which often results in exposure to high levels of particulate matter for a short period of time. Kochi et al. (2008) compare results from various studies that have looked at the health effects of the two different types of exposure, and have found that the morbidity impacts can be quite different.

Other studies that have specifically estimated dose-response functions from wildfire smoke still rely on a cost of illness approach, monetizing the costs of medical care, work days lost, and sometimes reduced activity days resulting from the morbidity effects of wildfire smoke (Hon 1999; Shahwahid and Othman 1999; Cardosa de Mendonça et al. 2004). But this represents an incomplete measure of the economic costs associated with wildfire smoke induced morbidity. First, health effects resulting from wildfire smoke may cause disutility to their recipient, and this would not be included in a simple cost of illness approach. Second, many residents in wildfire-prone areas know of the potential risks associated with wildfire smoke and take actions to protect themselves against it. Even if they do not know the potential risks, residents in areas exposed to wildfire smoke are often issued smoke advisory warnings which inform them of actions they can and should take to avoid health damage. As explained by Cropper (1981) the damage function approach ignores the fact that individuals can invest time and/or money in taking preventative actions to influence the time they spend ill. Further, she explains that an improvement in air quality will decrease the preventative actions that will be taken, and this needs to be included when valuing the benefits of pollution control. Two of the studies mentioned above did adjust their cost of illness measure in an attempt to capture the true WTP for reduced morbidity using an assumed WTP to cost of illness ratio of 2 to 1 (Hon 1999; Ruitenbeek 1999). However, there is an overall lack of literature on the true economic cost of health damages from wildfire smoke.

The contribution of this study is twofold. First, using data from the largest wildfire in Los Angeles County's modern history, we apply the averting behavior method and contingent valuation method to estimate the willingness-to-pay for a reduction in wildfire-smoke induced symptom days for the first time to our knowledge. Second, using the same data set, we compare estimates across all three common approaches used to value the economic cost of health damages from an air pollutant: the cost of illness approach, the averting behavior method and the contingent valuation method. The remainder of this article is organized as follows: Section II outlines the theoretical models motivating the analysis. Section III discusses the sample frame and data used in the analysis. Section IV presents the econometric estimation and results and Section V outlines conclusions and areas for future research.

II. Theoretical Framework

Averting Behavior Method

The averting behavior method is a revealed preference method that has been used in the field of health and environmental economics for many years. The method is based off of a health production function first outlined by Grossman (1972) with extensions to the model undertaken by Cropper (1981) and Harrington and Portney (1987). The basic idea of the averting behavior method in this health production function framework is that an individual experiences some health output, such as a number of days spent sick or some occurrence of symptoms, that enters into their utility function, causing disutility. This health output is in turn influenced by various factors, such as pollution levels, the individual's overall stock of health, demographic factors, lifestyle factors and finally, both averting and mitigating actions taken by the individual to decrease the chance they experience a negative health outcome. Averting and mitigating actions are somewhat different. The former are actions taken to decrease the chance of being exposed to some pollutant that causes the negative health outcome, such as filtering your water or staying indoors. The latter represent actions that are taken after experiencing the health outcome in an effort to mitigate its negative effects, such as going to the doctor or taking medications. This information can then be used to calculate the WTP to avoid a pollutant in general, or the symptoms that result from exposure to the pollutant. This method and the theoretical framework underlying it are explained in detail in Freeman (2003) and Dickie (2003). A simple one period illustration is outlined as follows: an individual's utility can be expressed by:

(1) $U = U(X, L, S)$

where X represents consumption of a composite market good with price normalized to 1, L represents leisure time, and S represents time spent sick. We can assume that utility is increasing in consumption and leisure and decreasing in sick time. An individual 'produces' this sick time according to a health production function as follows:

(2) $S = S(P, A, M, Z)$

where P represents exposure to a pollutant, A represents averting activities that can be taken to decrease exposure to the pollutant, M represents mitigating activities that can be taken to reduce the time spent sick and Z represents a set of exogenous factors that can affect the time spent sick, such as demographic factors and health status prior to exposure. It can be assumed that sick time is increasing in exposure to the pollutant and decreasing in averting and mitigating actions. Individuals also face a budget constraint as follows:

(3) $I = X + (p_a*A) + (p_m*M)$

where I represents labor and non-labor income, p_a represents the price of averting activities and p_m represents the price of mitigating activities. Therefore, the individual's utility maximization problem becomes:

(4) $$Max\ U = U\ (X, L, S\ (P, A, M, Z))$$

$$\text{s.t. } I = X + (p_a{*}A) + (p_m{*}M)$$

After solving for the first order conditions for a maximum and through substitution we can arrive at a marginal value of reduced pollution equal to (see Freeman (2003) for a full derivation):

(5) $$-p_a\ [(\partial S/\partial P) / (\partial S/\partial A)]$$

Or a marginal value of reduced illness equal to:

(6) $$-p_a / (\partial S/\partial A)$$

Which says the marginal WTP for a reduction in time spent sick can be calculated as the price of any averting or mitigating activity divided by the marginal effect of the use of that averting or mitigating activity on time spent sick.

Contingent Valuation Method

Unlike the averting behavior method which questions individuals about their actions to arrive at a measure of the economic value of a decrease in symptom days or the pollutant that causes them, the contingent valuation method uses a stated preference approach to estimate this value. In a contingent valuation framework, individuals are asked directly about the value they place on a specific change in a nonmarket good, which in this case would be a decrease in the level of a specific pollutant or a decrease in the number of symptom days experienced as a result of the pollutant. We assume individuals choose to maximize utility subject to a budget constraint as follows:

(7) $Max\ U(X, S)$

$$s.t.\ I = P_x * X + P_s * S$$

where I is the individual's income, X is a vector of market goods, Px is the vector of prices of the market goods, S is the individual's time spent sick, and Ps is the price of time spent sick. Solving this equation results in a set of Marshallian demand functions for the market goods. If we plug these demand functions into the individual's utility function and invert this function we arrive at a conditional expenditure function which shows the minimum expenditure that must be made on market goods to achieve some level of utility. Solving this dual problem of minimizing expenditures subject to a certain level of utility, say $u*$, results in a set of Hicksian demand functions as follows:

(8) $X* = X_h\ (P_x, P_s, S, u*)$

Substituting these into the expenditure function shows the minimum expenditure that must be made on all goods, to remain at utility level $u*$.

(9) $e = e\ (P_x, P_s, S, u*)$

The individual's marginal willingness-to-pay for a decrease in time spent sick can then be expressed as $-\partial e/\partial S$, the increase in expenditure given the decrease in time spent sick that allows the individual to maintain the same level of utility $u*$. Finally, the individual's willingness to pay for a decrease in time spent sick from S to S* can be expressed as:

(10) $WTP = e\ (P_x, P_s, S, u*) - e\ (P_x, P_s, S*, u*)$

In this article, we are interested in comparing the value of decreased morbidity from wildfire smoke across all three methodologies; the cost of illness (COI) approach, the averting behavior method and the contingent valuation method. As explained above, it has been repeatedly found that the cost of illness approach underestimates the true economic costs of health effects from various pollutants. However, the expected relationship between contingent valuation and averting behavior WTP for reduced morbidity is unclear. Comparing results from previous studies, Dickie et al. (1987) find that WTP estimates using the contingent valuation method (CVM) to value reductions in symptoms from ozone exposure are found to be 5 to 10 times larger than WTP estimates using the averting behavior method (ABM) valuing reductions in similar symptoms, but there is no theoretical support for this finding. Rather, they explain that averting behavior estimates could theoretically be larger due to the fact that many averting behaviors provide a direct source of utility to individuals. Therefore, the hypothesis we would like to test is as follows.

$$H_o: COI = WTP_{ABM} = WTP_{CVM}$$

$$H_a: COI < WTP_{ABM} ? WTP_{CVM}$$

III. Sampling Frame and Data

The Station Fire

The Station Fire began on Wednesday, August 26, 2009 in the Angeles National Forest, located adjacent to the Los Angeles, CA metropolitan area. The fire became increasingly difficult to contain due to hot weather conditions, thick brush, as well as rugged and steep terrain faced by firefighters. The fire was considered very dangerous and given the status of extreme growth potential from the start, a warning which proved all too true after the blaze doubled in size in a mere 5 days after it began. By the time the Station Fire was fully contained 52 days later on October 16, it had burned 160,577 acres, killed two firefighters, injured 22 people, and destroyed 209 structures, 89 of which were homes. While the fire burned, it threatened 12,000 residences and forced the evacuation of thousands of people in surrounding communities from their homes

(InciWeb 2009). The Station Fire was the largest in Los Angeles County's modern wildfire history and the tenth largest in California's.

The smoke from the Station Fire caused nearby residents to experience unhealthy air quality levels and as a result, smoke advisory warnings were issued by the South Coast Air Quality Management District (AQMD). These warnings advised residents to avoid vigorous outdoor and indoor exertion, stay indoors and run the air conditioner (AQMD 2009). Children, the elderly, and people with preexisting heart and lung conditions are most susceptible to health effects from wildfire smoke.

Sample

To collect data to implement these methods, a survey was created in the summer of 2009 and focus groups were held in Anaheim, California in the same summer. These focus groups focused on nearby residents' experience with the Freeway Complex Fire of 2008. Approximately six weeks after the Station Fire began, a revised survey was mailed to a random sample of residents in five cities in the vicinity of the Station Fire. The five cities were chosen based on having had a smoke advisory warning issued and the availability of air quality monitoring data to confirm that the cities were impacted by the wildfire smoke. The cities were also far enough away from the fire that it was unlikely residents' homes were damaged or destroyed. We wanted survey respondents to focus on the health effects from the wildfire smoke rather than the damages from the fire itself. Two follow-up mailings were implemented for a total of three mailings to non-respondents. The initial sample size was 1000 individuals, 40 surveys were not deliverable, and 456 complete surveys were returned for an overall response rate of 47.5%.

To gather data to implement the averting behavior model, the survey questioned respondents about the health effects they experienced during the fire, the time spent on averting and mitigating actions, along with the costs of these actions where appropriate, the respondents health history, lifestyle factors, and demographic information. Various averting activities were presented to respondents, and they could choose the amount of time they spent on each one. These activities were chosen based on recommendations from the Center for Disease Control on what to do during a fire to decrease exposure to the smoke, as well as what previous studies have found in regards to the actions people take during wildfires (Mott et al. 1999; Kunzli et al. 2006).

For the contingent valuation WTP model, respondents were asked about their willingness-to-pay to reduce the health symptoms their household experienced by 50%. We used a dichotomous choice question format with 10 different bid amounts ranging from $10-$750 based on focus groups and acute morbidity values from various studies summarized in Dickie and Messman (2004). As pointed out by Alberini et al. (1997), information on the duration and severity of the illness should also be collected. A summary of all variables and their sample means can be found in Table 1.

Interestingly, 38% percent of respondents experienced some kind of symptom from the wildfire smoke and 43% respondents had at least one household member that experienced at least one symptom. Table 2 outlines the percentage of survey respondents experiencing each type of symptom. In an averting behavior model, the assumption is that individuals take actions to decrease their exposure to a pollutant and according to Freeman (2003), in order for the approach to be accurate, individuals must believe that the pollutant at hand can cause illness. In addition, we should know individual’s beliefs about the effectiveness of these activities. Our data shows that 89% of respondents took some kind of averting action during the Station Fire.

Table 1: Variable Definitions and Means

Type of Variable	Variable	Definition	Coding	Mean
Experience with Fire	DAYS_SMELL_SMOKE_OUT	number of days smoke was smelled outside the home	1=1-5 days; 2=6-10 days; 3=11-15 days; 4=more than 15 days	2
	DAYS_SMELL_SMOKE_IN	number of days smoke was smelled inside the home	1=1-5 days; 2=6-10 days; 3=11-15 days; 4=more than 15 days	0.91
Averting Activities Taken During the Fire	AV_EVAC	evacuated	1= yes, 0= no	0.06
	AV_MASK	covered face with a mask	1= yes, 0= no	0.07
	AV_CLEAN	used an air filter, air cleaner or humidifier	1= yes, 0= no	0.2
	AV_NOWORK	avoided going to work	1= yes, 0= no	0.05
	AV_ASH	removed ashes from property	1= yes, 0= no	0.58
	AV_A/C	ran air conditioner more than usual	1= yes, 0= no	0.62
	AV_INDOORS	stayed indoors more than usual	1= yes, 0= no	0.75
	AV_NOREC	avoided normal recreation activities/exercise	1= yes, 0= no	0.8
Beliefs	EFFECTIVE	belief that averting actions taken were very effective in reduing or eliminating health effects from the smoke	1= yes, 0= no	0.49
	LITTLE_EFFECTIVE	belief that averting actions taken were a little effective in reduing or eliminating health effects from the smoke	1= yes, 0= no	0.25
	HEAR_READ	heard or read about health effects of wildfire smoke during the fire	1= yes, 0= no	0.87
	SMOKE_AFF	belief that wildfire smoke can affect a person's health	1= yes, 0= no	0.91
*Illness Information**	SYMP_PEOP	number of people in household who experienced health effects from the smoke	continuous	0.91
	EAR_NOSE_THROAT_SYMP	ear, nose and throat symptoms, such as cough, sore throat, burning eyes, runny nose, sinus problems, etc.	1= yes, 0= no	0.35
	BREATHE_SYMP	breathing symptoms, such as shortness of breath, aggravation of asthma, bronchitis, emphysema, etc.	1= yes, 0= no	0.18
	HEART_SYMP	heart symptoms, such as rapid heartbeat, chest pain, etc.	1= yes, 0= no	0.04
	OTHER_SYMP	other symptoms, such as anxiety, nausea, dizziness	1= yes, 0= no	0.08
	SYMP_DAYS	total number of days symptoms were experienced	continuous	2.68
	PAIN	level of pain from symptoms	scale of 1(no pain) - 5 (severe pain)	0.98
*Mitigating Activities Taken as a Result of Symptoms**	DOC	obtained medical care (physician, urgent care, ER, hospital)	1= yes, 0= no	0.03
	NONTRAD	visited a non-traditional health care provider	1= yes, 0= no	0.01
	NONPRESC	took nonprescription medications	1= yes, 0= no	0.12
	MISS_WORK	missed work	1= yes, 0= no	0.04
	MISS_REC	missed recreation days	1= yes, 0= no	0.28
Health and Lifestyle	EXERCISE	number of times per week of exercise	0=0 times per week; 1=1-2 times per week; 2=3-5 times per week; 3=more than 5 times per week	1.63
	INREC_HRS	number of hours per week or indoor recreation	continuous	2.82
	OUTREC_HRS	number of hours per week of outdoor recreation	continuous	4.74
	ALCOHOL	alcoholic drinks per week	0=none; 1=1-7 times per week; 2=8-14 times per week; 3=more than 14 times per week	0.6
	SMOKE_NOW	currently a smoker	1= yes, 0= no	0.08
	EXCELLENT	current health is excellent	1= yes, 0= no	0.3
	GOOD	current health is good	1= yes, 0= no	0.54
	POOR	current health is poor		0.01
	REG_DOC	visit a physician once a year or two for check-ups	1= yes, 0= no	0.88

Table 1 continued

Type of Variable	Variable	Definition	Coding	Mean
Health and Lifestyle	PAST_RESP_PROB	diagnosed in the past with a chronic respiratory disease	1= yes, 0= no	0.19
	RESP_PROB_NOW	respiratory disease still present in past 12 months	1= yes, 0= no	0.12
	PAST_HRT_PROB	diagnosed in the past with a heart disease	1= yes, 0= no	0.13
	HRT_PROB_NOW	heart disease still present in past 12 months	1= yes, 0= no	0.08
	PAST_FIRE_SMOKE	experienced health effects from smoke from prior fires	1= yes, 0= no	0.23
Demographics	MALE	sex of respondent	1=male, 0=female	0.61
	MARRIED	married	1=yes, o=no	0.7
	AGE	age of respondent	continuous	58
	WHITE	race of respondent	1=white, o=other	0.78
	YRS_EDU	years of education	8=eighth grade or less, 10=some high school, 12=high school graduate, 14=some college, 16=college or teachnical school graduate, 18=some graduate school, 20=advanced degree	15.81
	EMPLOY_FULL	employed full time	1= yes, 0= no	0.53
	EMPLOY_PART	employed part time	1= yes, 0= no	0.07
	NOT_EMPLOY	unemployed or retired	1= yes, 0= no	0.4
	INC	income	15=less than 19,999; 25=20,000-29,999; 35=30,000-39,999; 45=40,000-49,999; 55=50,000-59,999; 65=60,000-69,999; 75-70,000-79,999; 85=80,000-89,999; 95=90,000-99,999; 125=100,000-149,999; 175=150,000-199,999; 200=more than 200,000	84.04
	DUARTE	live in Duarte, CA	1= yes, 0= no	0.14
	MONROVIA	live in Monrovia, CA	1= yes, 0= no	0.21
	SIERRA MADRE	live in Sierra Madre, CA	1= yes, 0= no	0.06
	BURBANK	live in Burbank, CA	1= yes, 0= no	0.21
	GLENDORA	live in Glendora, CA	1= yes, 0= no	0.38

Table 2: Health Symptom Profile for Survey Respondents

Symptom	Percentage of Survey Respondents
Ear, nose or throat symptoms	36
Breathing symptoms	18
Heart symptoms	4
Other symptoms	9

In addition, 90% of respondents said they did believe smoke from the Station Fire could affect a person's health, while the other 10% reported that they did not know. The percentage of respondents that took each averting or mitigating action can be found in Table 3.

Table 3: Averting and Mitigating Actions Taken by Respondents

Averting Actions	**Percentage of Survey Respondents**
Evacuated	5
Wore a mask	7
Used an air cleaner, filter or humidifier	21
Avoided going to work	5
Removed ashes from property	57
Ran air conditioner more than usual	60
Stayed indoors more than usual	73
Avoided normal outdoor recreation/exercise	78
Mitigating Actions	
Obtained medical care	4
Went to non-traditonal health provider	1
Took non-prescription medicines	13
Missed work	4
Missed recreation activities	28

IV. Econometric Estimation

Averting Behavior Model

In empirical estimation of a health production function, the health outcome experienced is the dependent variables of interest. This can be modeled in various ways, such as whether or not a symptom was experienced, how many symptoms were experienced, or for how many days symptoms were experienced. We chose to focus on the latter to stay consistent with our contingent valuation question. The independent variables include everything that enters the right hand side of the health production function, including exposure to the pollutant, the averting and mitigating actions taken, the individual's health history, lifestyle factors and demographic factors. However, estimating this model has proven somewhat difficult in practice. A major issue that comes up in empirical estimation, explained thoroughly by Dickie (2003) is the fact that there are endogenous variables (averting and mitigating behaviors) on the right hand side of the health production function. These activities are chosen by the respondent rather than being exogenous, so the issue of simultaneous equations arises. These endogenous regressors will be correlated with the disturbance of the illness equation they appear in, meaning least squares estimators will be both biased and inconsistent. Numerous studies that have estimated health production function models over the years have expressed the importance of this issue (Gerking and Stanley 1986; Joyce et al. 1989; Alberini et al. 1996; Bresnahan et al. 1997; Dasgupta 2004; Dickie 2005).

This issue of endogeneity is complicated by the fact that the dependent variable and the averting and mitigating behavior variables are often discrete or count variables in nature, meaning nonlinear estimation techniques must be used. For our study, the averting activities taken by respondents were modeled as binary variables (whether or not the activity was taken). Our dependent variable, the number of days symptoms from the wildfire smoke were experienced, is count in nature. To address this issue of endogeneity in a nonlinear framework, we employ two approaches to estimation, both using an instrumental variables approach. The first is a nonlinear analogue to two-stage least squares, similar to the approach taken by Gerking and Stanley (1986) and tested by Windmeijer and Silva (1997). In the first stage, the reduced form regressions for each of the endogenous variables (averting and mitigating actions) are estimated separately. In the second stage, the illness equation is estimated by replacing the endogenous variables with their predicted values from the first stage reduced form regressions. The second approach employs the exact same first stage regression models but in the second stage, the illness equation is estimated by including the original endogenous variables and the first stage residuals for each of these variables. Terza et al. (2008) refer to these approaches as two-stage predictor substitution (2SPS) and two-stage residual inclusion (2SRI), respectively. In a general parametric framework the authors find that 2SRI is consistent and 2SPS is not.

The averting actions that a large enough percentage of the sample undertook (AV_CLEAN, AV_ASH, AV_A/C, AV_INDOORS, and AV_NOREC) were estimated as binary variables in a probit regression framework including all of the variables that would enter the illness equation as well as a set of identifying instrumental variables. The choice of these variables is somewhat subjective, but Dickie (2003) recommends variables such as wage, income, prices of averting activities, and other demographic or attitudinal variables that could affect the decision to undertake an averting action. In our survey, this includes such variables as INC, EMPLOY_FULL, EFFECT, LITTLE_EFFECT, and SMOKE_AFFECT. After finding that AV_ASH could not be significantly determined with a large enough combination of these variables, this averting action was removed from the equation.

Given that the dependent variable in the second stage of the averting behavior model, the number of symptom days experienced, is a count variable, a Poisson regression model was first used to estimate this illness equation. However, given that the variance of the dependent variable is much larger than the mean, a negative binomial model was estimated. A likelihood ratio test of the measure of the dispersion of the predictions confirms that the negative binomial model is more appropriate than the Poisson. After removing explanatory variables, including averting actions that continuously came in insignificant in the health production function model (AV_AC, AV_INDOORS and AV_NOREC), the results of the 2SPS and 2SRI negative binomial models can be found in Table 4[1]

Table 4: Negative Binomial Estimation of Health Production Function for Number of Symptom Days

Variable	2SPS	P>|z|	2SRI	P>|z|
CONSTANT	-2.631	0.00001	-2.613	0.00001
DAYS_SMELL_SMOKE_OUT	0.542	0.00001	0.539	0.00001
EAR_NOSE_THROAT_SYMP	2.982	0.00001	2.981	0.00001
BREATHE_SYMP	0.619	0.00001	0.616	0.00001
OTHER_SYMP	0.861	0.001	0.863	0.001
EXERCISE	-0.254	0.00001	-0.254	0.00001
ALCOHOL	0.173	0.038	0.176	0.035
REG_DOC	0.493	0.016	0.475	0.021
PAST_RESP_PROB	1.148	0.00001	1.155	0.00001
RESP_PROB_NOW	-1.074	0.00001	-1.086	0.00001
PAST_HRT_PROB	-1.206	0.003	-1.228	0.002
HRT_PROB_NOW	1.551	0.00001	1.562	0.00001
PAST_FIRE_SMOKE	0.276	0.034	0.281	0.031
MALE	-0.493	0.00001	-0.498	0.00001
BURBANK	0.379	0.023	0.383	0.021
GLENDORA	0.292	0.042	0.302	0.036
AV_CLEAN[a]	-1.685	0.003		
AV_CLEAN			-1.678	0.003
AV_CLEAN Residuals[b]			1.544	0.008
Log Likelihood	-450.206	Log Likelihood	-449.743	
LR chi2(16)	439.88	LR chi2(17)	440.81	
Prob > chi2	0.00001	Prob > chi2	0.00001	

[a] Predicted values of AV_CLEAN from the reduced form probit model
[b] Residuals from the reduced form probit model of AV_CLEAN

[1] A Hausman specification test was used to test for endogeneity of the AV_A/C regressor. The 2SPS estimates were compared with one-stage estimates uncorrected for the endogeneity. The p-value of 0.008 for this test indicates that the null hypothesis that both estimators are consistent can be rejected at the 1% level. Since instrumental variables estimators are consistent, we conclude that correcting for the endogeneity is necessary.

As expected, the number of days the respondent smelled smoke outside the home has a positive effect on the expected number of symptom days, holding all other variables constant. In addition, if the respondent experienced ear, nose, or throat symptoms, breathing symptoms, or other symptoms such as nausea or anxiety, this also has a positive effect on the expected number of symptom days, compared to heart symptoms. The more exercise the respondent engages in a typical week has a negative effect on the expected number of symptom days experienced. The more alcohol the respondent drinks has a positive effect on the expected number of symptom days. If the respondent visits the doctor regularly for checkups this also has a positive effect on expected number of symptom days. In addition, having a past respiratory problem or a current heart problem has a positive effect on expected symptom days, as expected. However, having a current respiratory problem or a past heart problem has a negative effect on expected symptom days. This result is not consistent with predictions, but may have to do with the fact that people with these conditions took more actions to prevent exposure to the wildfire smoke and thus experienced less symptom days. In addition, being a male has a negative effect on the expected number of symptom days. Living in Burbank or Glendora during the fire had a positive effect. Finally, using an air cleaner/filter/humidifier more has a negative effect on the expected number of symptom days experienced, so this is the averting action used to calculate the respondent WTP for a decrease in symptom days.

Contingent Valuation Model

In using a contingent valuation framework with a dichotomous choice question format to value a decrease in the number of symptom days experienced from a pollutant, the yes/no willingness-to-pay response can be regressed on the bid amount and any variables that would enter the health production function. Freeman (2003) explains that technically you do not need to include other variables besides the bid amount in the model, but if willingness-to-pay does vary with other characteristics such as health status and demographics, this information should be known if the values from this study are to be used to value the benefits of pollution control in other contexts. Our original contingent valuation survey question represents a household, rather than an individual, measure of WTP. We first questioned respondents on whether any members of their household experienced health symptoms from the smoke from the Station Fire and then asked them if they would be willing to pay a specified amount to reduce the symptoms experienced by any members of the household by 50%.

We estimated a logistic regression model and after removing variables that continually came in insignificant in determining the predicted probability of WTP, the results of two model specifications can be found in Table 5.

Table 5: Logistic Regression of WTP for 50% Reduction in Household Symptom Days

Variable	Model 1	P>|z|	Model 2	P>|z|
CONSTANT	0.919	0.226	-0.826	0.068
BID	-0.0051	0.0001	-0.004	0.0001
LOG HALF_HH _SYMP_DAYS	0.505	0.038	0.487	0.031
AVERT_COST	0.001	0.007		
INSURANCE	-1.733	0.011		
GLENDORA	-0.77	0.085		
Log Likelihood	-77.425	Log Likelihood	-86.689	
LR chi2 (5)	40.86	LR chi2 (2)	22.34	
prob > chi2	0.00001	prob > chi2	0.00001	

Given that the WTP response is for the household, the total number of symptom days experienced by all household members were added together. Since respondents were valuing a 50% reduction in these symptom days, this variable was divided by two to arrive at the final good being valued, half of all symptom days experienced in the household (HALF_HH_SYMP_DAYS). Model 1 includes all statistically significant variables related to the respondents' health status and demographic information and model 2 includes only the WTP bid amount and the number of household symptom days. Given that this WTP response is for a reduction in household symptom days, it is not surprising that many of the explanatory variables did not come in statistically significant in explaining willingness-to-pay. The bid coefficient in each model is negative and statistically significant. Similar to Alberini et al. (1997) we find that the log of the household symptom days in each model is positive and the probability that the respondent is WTP increases at a decreasing rate with this variable.

Given that this is a model of household willingness-to-pay whereas the averting behavior method is valuing an individual willingness-to-pay measure, we divided the contingent valuation WTP bid amount by the number of household members who experienced symptoms from wildfire smoke in an attempt to get at an individual value (INDIVIDUAL_BID). The results of this logistic regression model including only those variables which were statistically significant in explaining the predicted probability of WTP can be found in Table 6.

Table 6: Logistic Regression of WTP for 50% Reduction in Individual Symptom Days

Variable	Model 3	P>|z|	Model 4	P>|z|
CONSTANT	0.601	0.364	0.04	0.859
INDIVIDUAL_BID	-0.008	0.001	-0.007	0.001
YOU_BREATHE	0.965	0.012		
HEART_NOW	0.953	0.099		
INSURANCE	-1.181	0.068		
Log Likelihood	-83.837	Log Likelihood	-90.853	
LR chi2 (4)	35.69	LR chi2 (1)	21.65	
prob > chi2	0.00001	prob > chi2	0.00001	

Comparison of Values for Reductions in Symptom Days

Cost of Illness

The simple cost of illness estimate for the sample of respondents who experienced health symptoms was calculated by adding together the cost of medical visits and prescribed medications, the cost of non-prescription medicines, the cost of any visits to a non-traditional health provider, the opportunity cost of time spent in obtaining medical care, and lost wages from being unable to work. Dividing this total cost by the number of days the individual experienced symptoms results in a daily cost of illness estimate. Taking the average across the whole sample of respondents who experienced symptoms from the wildfire smoke results in a final cost of illness estimate of about $3 per symptom day.

Averting Behavior Method

In the averting behavior regression model, WTP for a given change in illness can be calculated as $[p_a / (\partial S/\partial A)]$ from equation (6). Given that using an air cleaner/filter/humidifier (AV_CLEAN) was the only averting action that had a statistically significant and negative effect on symptom days, the WTP measure is based on this action. To estimate the daily price of this averting action, p_a, we calculated the average cost reported by those respondents who took this action and arrived at a price of $43. The marginal effect of this variable on symptom days is -1.00 in the 2SPS model and -0.677 in the 2SRI model. The WTP value to avoid one day of wildfire-induced symptom days is estimated as $43.00 for the 2SPS model and $93.83 for the 2SRI model.

Contingent Valuation Method

Turning to the contingent valuation logistic regression models, the mean WTP when WTP is greater than or equal to zero can be calculated as $ln(l + exp^{a})/\beta$ where α is the sum of all variable coefficients except the bid amount times their sample means and β is the absolute value of the coefficient on the bid amount. For the household WTP models in Table 5, by plugging one day of symptoms into the model instead of the mean symptom days, we can estimate the value for a one day reduction in symptom days. Model 1 results in a mean WTP value of $74.22 and model 2 results in a mean WTP value of $90.64 for a one day reduction in symptom days. For the individual WTP model in Table 6, model 3 results in a mean WTP estimate of $74.51 and model 4 results in a mean WTP value of $98.13.

A summary of these estimates can be found in Table 7. As expected, cost of illness estimates are considerably lower than WTP estimates for a reduction in symptom days. Given our results, it appears that we cannot reject the null hypothesis that $WTP_{ABM} = WTP_{CVM}$ but further analysis is needed to compare confidence intervals of these estimates.

Table 7: Values for Reductions in 1 Wildfire Smoke Induced Symptom Day

	Cost of Illness	ABM WTP	CVM WTP
Individual	$3	$43 & $94	$75 & $98
Household			$74 & $91

Caution should be used in comparing WTP estimates across the contingent valuation method and the averting behavior method due to the different samples used. The CVM WTP estimate is based on a sample which includes only those respondents whose households experienced health symptoms from the wildfire smoke whereas the averting behavior method is based on a sample of all survey respondents, whether they experienced symptoms or not. In addition, given the findings of Terza et al. (2008) we would recommend the averting behavior WTP estimate based on the 2SRI model be used ($94) given the superiority of this econometric estimation technique over 2SPS.

Our averting behavior and contingent valuation WTP results do fall within the range of those summarized in Dickie and Messman (2004) to avoid one day of symptoms, although we do not distinguish between type of symptoms experienced. This will be an important area of future research with this data set.

V. Conclusion

The economic costs of the morbidity effects resulting from exposure to wildfire smoke represent an important but often unknown aspect of the damages caused by a given wildfire. If future fire management policies are to be accurately evaluated, the costs of these damages need be monetized and included in decision-making. Given that the smoke released by wildfires causes a short period of high exposure to particulate matter, it may be inaccurate to use previously estimated dose-response functions obtained from non-wildfire particulate matter exposure to estimate these costs. Further, even if dose-response functions are estimated specifically for wildfire smoke exposure, the resulting cost of illness estimates will largely underestimate the value of reduced morbidity from wildfire smoke because they ignore critical components of this value such as decreases in disutility and behavioral responses. The comparison of cost of illness and willingness-to-pay estimates from this study confirm these theoretical predictions. An important area of future research should include estimating willingness-to-pay values for reductions in days of specific symptoms experienced as a result of wildfire smoke exposure.

References

Alberini, A., G. Eskeland, A. Krupnick, and G. McGranahan. 1996. "Determinants of Diarrheal Disease in Jakarta." *Water Resources Research*, 32(7), 2259-2269.

Alberini, A., M. Cropper, T. Fu, A. Krupnick, J. Liu, D. Shaw, and W. Harrington. 1997. "Valuing Health Effects of Air Pollution in Developing Countries: The Case of Taiwan." *Journal of Environmental Economics and Management* 34: 107-126.

Alberini, A. and A. Krupnick. 1998. "Air Quality and Episodes of Acute Respiratory Illness in Taiwan Cities: Evidence from Survey Data." *Journal of Urban Economics* 44(1): 68-92.

Alberini, A. and A. Krupnick. 2000. "Cost-of-Illness and Willingness-to-Pay Estimates of the Benefits of Improved Air Quality: Evidence from Taiwan." *Land Economics* 76(1): 37-53.

Anaman, K.A. 2001. “Urban Householder’s Assessment of the Causes, Responses, and Economic Impact of the 1998 Haze-Related Air Pollution Episode in Brunei Darussalam.” ASEAN Economic Bulletin 18(2): 193-205.

AQMD. South Coast Air Quality Management District. “Wildfire Smoke Continues to Cause Unhealthy to Hazardous Air Quality in Foothill and Mountain Areas Near Fire.” August 31, 2009. <http://www.aqmd.gov/news1/2009/smokeadvisory08-31-09.htm> (accessed 12/09).

Berger, M., G. Blomquist, D. Kenkel, and G. Tolley. 1985. “Valuing Changes in Health Risks: A Comparison of Alternative Measures.” *Southern Economic Journal* 53(4): 967-984.

Berrens, R.P., A.K. Bohara, H.C. Jenkins-Smith, C. Silva, and D.L. Weimer. 2004. “Information and Effort in Contingent Valuation Surveys: Application to Global Climate Change Using National Internet Samples.” *Journal of Environmental Economics and Management* 47(2): 331-363.

Bresnahan, B., M. Dickie, and S. Gerking. 1997. “Averting Behavior and Urban Air Pollution.” *Land Economics* 73(3): 340-357.

Cardoso de Mendonça, M. J., M.d.C.V. Diaz, D. Nepstad, R. Seroa da Motta, A. Alencar, J.C. Gomes, and R.A. Ortiz. 2004. “The Economic Cost of the Use of Fire in the Amazon.” *Ecological Economics* 49(1): 89-105.

Cropper (1981). “Measuring the Benefits from Reduced Morbidity.” *The American Economic Review* 71(2): 235-240.

Dasgupta, P. 2004. “Valuing Health Damages from Water Pollution in Urban Delhi, India: A Health Production Function Approach.” *Environment and Development Economics* 9(1): 83-106.

Dickie, M. 2003. “Defensive Behavior and Damage Cost Methods.” In Champ, P.A., K.J. Boyle and T.C. Brown (Editors), *A Primer on Nonmarket Valuation.* Boston: Kluwer Academic Publishers, pp. 445-482.

Dickie, M. 2005. “Parental Behavior and the Value of Children’s Health: A Health Production Approach.” *Southern Economic Journal* 71(4): 855-872.

Dickie, M., S. Gerking, D. Brookshire, D. Coursey, W. Schulze, A. Coulson, and D. Tashkin. 1987. “Reconciling Averting Behavior and Contingent Valuation Benefit Estimates of Reducing Symptoms of Ozone Exposure.” In *Improving Accuracy and Reducing Costs of Environmental Benefit Assessments* (supplementary report), U. S. Environmental Protection Agency, Office of Policy, Planning, and Evaluation, Washington, D. C.

Dickie, M. and S. Gerking. 1991. “Valuing Reduced Morbidity: A Household Production Approach.” *Southern Economic Journal* 57(3): 690-702.

Dickie, M. and V.L. Messman. 2004. “Parental Altruism and the Value of Avoiding Acute Illness: Are Kids Worth More Than Parents?” *Journal of Environmental Economics and Management* 48(3): 1146-1174.

EPA. Environmental Protection Agency. Particulate Matter: Health and Environment, May 9, 2008. < http://www.epa.gov/pm/health.html> (accessed 03/10).

Freeman, M. 2003. *The Measurement of Environmental and Resource Values: Theory and Methods.* Resources for the Future, Washington, DC.

Gerking, S. and L. Stanley. 1986. “An Economic Analysis of Air Pollution and Health: The Case of St. Luis.” *Review of Economics and Statistics* 68(1): 115-121.

Grossman, M. 1972. “On the Concept of Health Capital and the Demand for Health Care.” *Journal of Political Economy* 80(2): 223.

Harrington, W. and P. Portney. 1987. “Valuing the Benefits of Health and Safety Regulation.” *Journal of Urban Economics* 22: 101-112.

Hon, P.M.L. 1999. Singapore. In D. Glover & T. Jessup (Eds.), *Indonesia's Fires and Haze: The Cost of Catastrophe*. Singapore: Institute of Southeast Asian Studies, pp. 51-85.

InciWeb. Incident Information System. Station Fire Update, September 27, 2009. <http://inciweb.org/incident/article/9640/> (accessed 12/09).

Joyce, T., M. Grossman, and F. Goldman. 1989. “An Assessment of the Benefits of Air Pollution Control: The Case of Infant Health.” National Bureau of Economic Research, NBER Working Papers #1928.

Kochi, I., J. Loomis, P. Champ, and G. Donovan. 2008. “Health and Economic Impact of Wildfires: Literature Review.” <http://www.fs.fed.us/rm/value/docs/health_economic_impact_wildfire.pdf>

Kunzli, N., E. Avol, J. Wu, W.J. Gauderman, E. Rappaport, E., et al. 2006. “Health Effects of the 2003 Southern California Wildfires on Children.” *American Journal of Respiratory and Critical Care Medicine* 174.

Loehman, E.T., S.V. Berg, A.A. Arroyo, R.A. Hedinger, J.M. Schwartz, M.E. Shaw, R.W. Fahien, V.H. De, R.P. Fishe, D.E. Rio, W.F. Rossley, and A.E.S. Green. 1979. “Distributional Analysis of Regional Benefits and Costs of Air Quality Control.” *Journal of Environmental Economics and Management* 6(3): 222-243.

Loehman, E.T. and V.H. De. 1982. “Application of Stochastic Choice Modeling to Policy Analysis of Public Goods: A Case Study of Air Quality Improvements.” *The Review of Economics and Statistics* 64(3), 474-480.

Mansfield, C., F.R. Johnson, and G. Van Houtven. 2006. "The Missing Piece: Valuing Averting Behavior for Children's Ozone Exposures." *Resource and Energy Economics* 28(3): 215-228.

Martin, W.E., V. Brajer, and Z. Zeller. 2007. "Valuing the Health Effects of a Prescribed Fire." In W. E. Martin, C. Raish & B. Kent (Eds.), *Wildfire Risk: Human Perceptions and Management Implications.* Resources for the Future, pp. 244-261.

Mott, J.A., P. Meyer, D. Mannino, S. Redd, E. Smith, C. Gotway-Crawford, E. Chase, and W. Hinds. 2002. "Wildland Forest Fire Smoke: Health Effects and Intervention Evaluation, Hoopa, California, 1999." *Western Journal of Medicine* 176(3): 157-162.

Mott, J. A., D.M. Mannino, C.J. Alverson, A. Kiyu, J. Hashim, T. Lee, K. Falter, and SC Redd. 2005. "Cardiorespiratory Hospitalizations Associated with Smoke Exposure During the 1997 Southeast Asian Forest Fires." *International Journal of Hygiene and Environmental Health* 208: 75-85.

Ready, R., S. Navrud, and W.R. Dubourg. 2001. "How Do Respondents with Uncertain Willingness to Pay Answer Contingent Valuation Questions?" *Land Economics* 77(3): 315-326

Rittmaster, R., W.L. Adamowicz, B. Amiro, and R.T. Pelletier. 2006. "Economic Analysis of Health Effects from Forest Fires." *Canadian Journal of Forest Research* 36(4): 868-877.

Ruitenbeek, J. 1999. "Indonesia." In D. Glover & T. Jessup (Eds.), *Indonesia's Fires and Haze: The Cost of Catastrophe*. Singapore: Institute of Southeast Asian Studies, pp. 86-129.

Shahwahid, M. H. O., and J. Othman. 1999. "Malaysia." In D. Glover & T. Jessup (Eds.), *Indonesia's Fires and Haze: The Cost of Catastrophe*. Singapore: Institute of Southeast Asian Studies, pp. 22-50.

Sutherland, E. R., B.J. Make, S. Vedal, L.N. Zhang, S. J. Dutton, J. R. Murphy, and P.E. Silkof. 2005. “Wildfire Smoke and Respiratory Symptoms in Patients with Chronic Obstructive Pulmonary Disease.” *Journal of Allergy and Clinical Immunology* 115(2): 420-422.

Terza, J.V., A. Basu, and P.J. Rathouz. 2008. “Two-Stage Residual Inclusion Estimation: Addressing Endogeneity in Health Econometric Modeling.” *Journal of Health Economics* 27(3): 531-543.

Windmeijer, F.A.G. and J.M.C. Santos Silva. 1997. “Endogeneity in Count Data Models: An Application to the Demand for Health Care.” *Journal of Applied Econometrics* 12(3): 281-294.