DISSERTATION

QUANTIFYING THE ECONOMIC HEALTH COST OF EXPOSURE TO WILDFIRE SMOKE: FOUR ESSAYS IN NON-MARKET VALUATION, METHODOLOGICAL COMAPARISONS, AND ECONOMETRIC METHODS TO ADDRESS ENDOGENEITY

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ABSTRACT

QUANTIFYING THE ECONOMIC HEALTH COST OF EXPOSURE TO WILDFIRE SMOKE: FOUR ESSAYS IN NON-MARKET VALUATION, METHODOLOGICAL COMAPARISONS, AND ECONOMETRIC METHODS TO ADDRESS ENDOGENEITY

Wildfires and their proximity to urban areas have become more frequent, yet few economic studies have looked closely at the welfare implications exposure to wildfire smoke has on affected individuals. Further, there is a growing concern that human health impacts resulting from this exposure are ignored in estimates of the monetized damages from a given wildfire. Current research highlights the need for better data collection and analysis of these impacts.

Using unique primary data, this dissertation quantifies the economic health cost of exposure to wildfire smoke using non-market valuation techniques including the contingent valuation and defensive behavior methods. The individual willingness to pay for a reduction in symptom days as well as perceived pollution levels are quantified and compared to a simple cost of illness estimate. Results indicate that many residents surveyed did not seek medical attention for major health effects, but rather suffered from minor health impacts whose cost is not captured in a cost of illness estimate. As a result, expenditures on defensive activities and the disutility associated with symptoms and lost leisure are found to be substantial for the case of wildfire smoke exposure.

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CHAPTER ONE

Introduction

The occurrence of wildfires represents both a tragic natural disaster to those negatively affected as well as a necessary ecological process which sustains healthy forest growth and habitat vitality. U.S. federal fire policy, which for much of the 20th century focused on suppressing all fires on national forests to protect nearby communities, has shifted to a new focus of balancing fire suppression with fire management and prevention practices. The updated Federal Wildland Fire Management Policy of 2001 recommends that federal fire management activities provide public safety, protect land management objectives and human welfare, integrate programs, emphasize the natural ecological role of fire, and contribute to ecosystem sustainability (NWCG, 2001).

Increased fire management practices such as prescribed fire, forest thinning, and community awareness and education can improve forest health and decrease the risk of wildfire to surrounding communities. As populations expand and individuals move closer to the forest fringe, there will undoubtedly be a push for better state and federal fire management and prevention practices. However, implementation is often constrained by funding and determining the appropriate amount of investment into these programs is a challenge.

As pointed out by Abt et al. (2008), while federal wildfire policy is often scrutinized, there is very little literature quantifying the economic costs and benefits resulting from wildfire, making accurate evaluation of wildfire programs extremely difficult. One of the nine guiding principles of the updated 2001 Policy is that "fire management programs and activities are economically viable, based upon values to be protected, costs, and land and resource management objectives" (NWCG, 2001). However, Butry et al. (2001) explain that there is no organization in the United States which attempts to quantify these complete economic impacts for a given wildfire.

There is a growing literature citing the need to incorporate critical impacts other than suppression costs and loss of property in damage assessments of a given wildfire, one of which is the cost of damages to human health from exposure to wildfire smoke (Abt et al., 2008; Butry et al., 2001; Dale, 2009; Zybach et al., 2009). Kochi et al. (2010) conducted an extensive review of the literature on the economic cost of health damages from wildfire smoke exposure and concluded that while this cost should be considered in wildfire management policy, the available research is scarce and incomplete.

While a number of studies have attempted to quantify the economic cost of the health effects of wildfire smoke exposure from wildfires throughout the world (Hon, 1999; Ruitenbeek, 1999; Shahwahid and Othman, 1999; Butry et al., 2001; Cardoso de Mendonça et al., 2004; Rittmaster et al., 2006; Martin et al., 2007), they have heavily relied on a cost of illness (COI) approach to monetize these damages, which has been found to largely underestimate the true economic cost of health damages from exposure to a pollutant. As explained by Freeman (2003), a pollutant that affects human health impacts well-being in four ways: incurred medical expenses and lost wages (also referred to as mitigating activities), expenditures on averting activities taken to avoid the health effects, and the disutility associated with symptoms or lost leisure. The cost of illness approach ignores these last two components.

If accurate evaluations of fire management programs are to be made, the theoretically correct measure of the cost of damages to human health from exposure to wildfire smoke should be monetized. This value is the individual willingness to pay (WTP) to avoid this damage, which can be calculated using two common approaches in the field of non-market valuation, the contingent valuation method (CVM) and the defensive behavior method (DBM), also referred to as the averting behavior method. It should be noted that a few of the above studies did adjust their cost of illness estimate using an assumed WTP: COI ratio, but this ratio has never been calculated for the specific case of wildfire smoke as no studies have attempted to quantify the willingness to pay to avoid this damage. Figure 1.1 visually shows the components that comprise the willingness to pay to avoid the health damages associated with exposure to a pollutant.

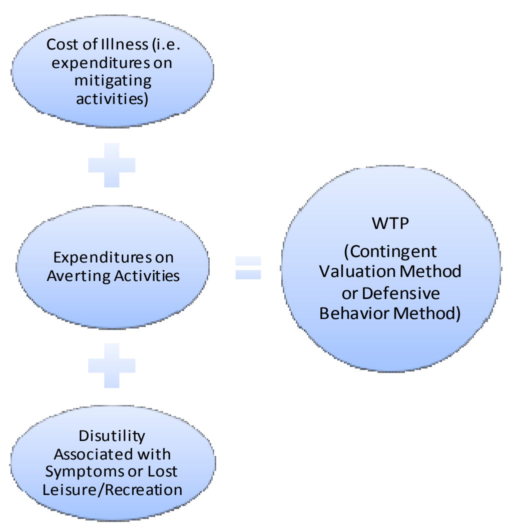

FIGURE 1.1
Components of Willingness to Pay to Avoid Health Damages

Branches of the U.S. EPA such as the National Center for Environmental Economics are responsible for analyzing the economic impacts, i.e. costs and benefits, of environmental regulations and policies. They recognize the inadequacies of relying on cost of illness estimates but explain that they continue to be used by the EPA due to the fact that many health effects are simply not studied from the willingness to pay perspective (U.S. EPA, NCEE).

This study applies both the contingent valuation and the defensive behavior method to calculate the willingness to pay for a reduction in symptom days and perceived pollution levels from wildfire smoke for the first time to our knowledge. Theory tells us that the cost of illness will provide a lower bound to this value, and here we attempt to quantify this discrepancy for the specific case of wildfire smoke. By conducting a survey of residents impacted by smoke during the largest wildfire in Los Angeles Counties' modern history, we look at the health effects experienced as a direct result of exposure to the wildfire smoke and all of the associated costs of this exposure. We quantify expenditures on medical care and the opportunity cost of time spent in obtaining it. The defensive actions individuals took to minimize their exposure to the smoke and the associated investments of time and money made are given considerable attention to determine whether the defensive behavior method is an appropriate application to wildfire smoke exposure. By comparing willingness to pay values with cost of illness estimates and expenditures on defensive activities, the value of the disutility associated with this exposure is quantified. In addition, we statistically compare willingness to pay estimates across both stated and revealed preference approaches, which provides a test of convergent validity. Finally, we explore econometric models to address endogeneity in a nonlinear framework, a common challenge to implementing the defensive behavior method.

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CHAPTER TWO

The Hidden Cost of Wildfires: Health Effects and Associated Costs from California's Station Fire of 2009

I. INTRODUCTION

As wildfire seasons increase in intensity and length in many parts of the western United States, it is becoming increasingly important to include the full cost of wildfire damages in any evaluation of future fire management policies. Nowhere does this issue seem more relevant than California, a state that has seen over three million acres of its land burned by wildfires since 2007 (CalFire). Increased levels of fire management and prevention practices are often proposed in California as a way to mitigate future losses from wildfires. These practices include vegetation management activities such as prescribed fire and forest thinning, community awareness and education, the creation of local and community Fire Safe Councils, and participation in the national Firewise/USA program. Although these practices may help to prevent losses from future wildfires, their implementation is often constrained by funding.

In determining whether increased funds for these practices are justified, policy makers need to be able to accurately evaluate the tradeoffs being made using sound economic analyses. At the federal level, The Federal Wildland Fire Management Policy of 1995 stresses the need to address economic efficiency of fire management and inform the public of the economic benefits of fuel treatment projects and the risks associated with not undertaking them (USDI-USDA, 1995). One of the nine guiding principles of the updated 2001 Policy is that “fire management programs and activities are economically viable, based upon values to be protected, costs, and land and resource management objectives” (NWCG, 2001). At the state level, California’s 2010 Strategic Fire Plan calls for the use of economically efficient fuels treatment projects such as prescribed fire and forest thinning.

However, the only way for policy makers to accurately evaluate fire management actions on an economic efficiency based criterion is to be fully aware of the economic benefits of each management action, which includes the economic costs associated with not taking the management action. While suppression costs and insured damages to homeowners are often reported as the main economic costs of wildfires, there is a growing concern that this represents a very incomplete measure of the cost of the damages from wildfires (Butry et al., 2001; Morton et al., 2003; Dale, 2009; Zybach et al., 2009). One of the main issues is that human health impacts from wildfire smoke are typically ignored in estimates of monetized damages.

Human health effects from wildfire smoke exposure have been talked about for decades but rarely quantified. Back in 1979 Gorte and Gorte in a USDA Forest Service technical report explained that economic justification of fire management expenditures have been called for since the 1920’s. They outline economic guidelines for determining how much should be spent to protect forests from fire and explain that the economically optimal level of funding for fire management based on a least-cost-plus-loss method are those that minimize the sum of wildfire suppression costs, presuppression costs, and resource losses, which includes damages to human health.[1] Twenty-two years later, Butry et al. (2001) explained that while this criterion outlined by Gorte and Gorte (1979) requires systematic calculations of the associated costs, losses and gains of a given wildfire, there is no organization in the United States which attempts to quantify these complete economic impacts.

More recently, Abt et al. (2008) suggested immediate improvements in data collection to be used in economic impact assessments for U.S. Forest Service wildfire programs. They call for more research to achieve consistent estimation of the various resource losses associated with wildfires, including human health impacts. The authors cited two studies which have attempted to quantify the economic cost of the health impacts of wildfire smoke, Butry et al. (2001) and Rittmaster et al. (2006), and concluded that further research needs to be done to allow estimation of health impacts from wildfire program activities. Kochi et al. (2010) conducted an extensive review of the literature on the economic cost of health damages from wildfire smoke exposure and concluded that while this cost should be considered in wildfire management policy, the available research is scarce and incomplete.

This study seeks to address this gap in the literature by outlining an empirical method to quantify the economic cost of health effects associated with wildfire smoke exposure which can be utilized in damage assessments of future wildfires. This method is demonstrated with a case study that quantifies the cost of health damages from exposure to wildfire smoke from California's Station Fire of 2009. The remainder of this paper is organized as follows: Section II presents the methods that can be adapted to calculate the

[1] Now referred to as the least-cost-plus-net-value-change method to recognize the fact that wildfires can also provide significant benefits.

economic cost of human health damages from exposure to wildfire smoke; Section III outlines the specific application of these methods to California's Station Fire of 2009, including a description of the study area, an explanation of the primary data collected for the study, pollution levels and descriptive statistics of the sample; Section IV presents an econometric approach to the analysis; Section V reports results of the analysis; Section VI outlines implications of this analysis.

II. METHODS FOR QUANTIFYING THE ECONOMIC COST OF HEALTH DAMAGES

The majority of studies that have attempted to quantify the cost of damages to human health from exposure to wildfire smoke have been limited to a cost of illness (COI) or damage function approach. The cost of illness approach sums resource and opportunity costs of being sick to arrive at a final cost of illness from exposure to a pollutant. These costs 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 data to estimate how various levels of a particular pollutant will affect human health outcomes (called dose-response functions) and then connects these health outcomes with previously obtained associated costs to arrive at a final cost of illness.

These two approaches have been applied to several wildfires around the world. Hon (1999), Shahwahid and Othman (1999) and Ruitenbeek (1999) calculated the economic cost associated with heath effects from the 1997 haze in Southeast Asia. Hon (1999) and Shahwahid and Othman (1999) estimated original dose-response functions to obtain predicted health outcomes caused by wildfires in Singapore and Malaysia and then connected these outcomes with country-specific costs of treatment to arrive at a final cost of illness. Ruitenbeek (1999) applied the estimated dose-response function from Shahwahid and Othman (1999) to translate the haze density in Indonesia into predicted health outcomes. The author then used economic costs from World Bank studies to calculate associated medical costs and the value of lost wages resulting from the wildfires and haze. Butry et al. (2001) used results obtained from Sorenson et al. (1999) on the health effects experienced during the 1998 Florida fires (asthma and bronchitis) and connected these with previously obtained estimates of medical expenditures to estimate the total cost of illness from these fires.

However, it has been well understood and documented for many years in the economics literature that the cost of illness and damage function methods underestimate the economic costs associated with health effects from exposure to a pollutant (Dickie, 2003; Freeman, 2003), including those contained in wildfire smoke. First, health effects resulting from wildfire smoke may cause disutility to their recipient, such as pain, discomfort, or a loss of recreation days and this would not be captured 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 costly defensive actions to protect themselves against it. During the 2003 Southern California wildfires, Kunzli et al. (2006) found that children with asthma were more likely to take preventative actions such as wearing masks and staying indoors to minimize their exposure to the smoke. Mott et al. (2002) found that during a 1999 wildfire in northern California near the Hoopa Valley National Indian Reservation, residents took actions such as wearing face masks, evacuating, running high-efficiency particulate air cleaners in the home and following public service announcements. 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 damages. As explained by Cropper (1981), an improvement in air quality will decrease the preventative actions that will be taken, and this cost savings needs to be included when valuing the benefits of pollution control. In a review of the literature on the economic cost of health damages from wildfire smoke, Kochi et al. (2010) concluded that a better understanding of preventative actions taken during wildfires is needed when evaluating the health related cost of wildfire smoke exposure.

If agencies are evaluating policies on an economic efficiency based criterion, the appropriate measure of the cost of health damages from exposure to wildfire smoke would be the full economic cost of these damages. The theoretically correct measure of this cost is the individual willingness to pay (WTP) to avoid this damage because it will include all costs individuals face when exposed to wildfire smoke: medical expenditures, lost wages, investments of time or money in taking preventative actions to decrease exposure, and the disutility associated with symptoms or lost leisure (Freeman, 2003). The cost of illness and damage function approaches ignore these last two components.

Only a handful of studies that estimate the economic cost of health effects from wildfire smoke exposure incorporate WTP values into their estimates. However, none of these WTP values were estimated for health damages avoided from wildfire smoke specifically. Martin et al. (2007) and Rittmaster et al. (2006) both used dose-response functions estimated in prior studies and connected estimated health outcomes with a mix of COI and WTP estimates from prior research to calculate the economic cost of health damages from a hypothetical prescribed fire in the Kaibab National Forest and the 2001 Chisholm Fire in Canada, respectively. Cardoso de Mendonça et al. (2004) estimated an original dose-response function and calculated the economic cost of health damages from fire used by farmers in the Amazon, applying WTP values transferred from Seroa de Motta et al. (2000a,b). Finally, the Hon (1999) and Ruitenbeek (1999) studies adjusted cost of illness estimates using an assumed WTP: COI ratio of 2:1. This ratio was taken from a range of WTP and COI estimates from the Asian Development Bank Workbook (1996) specifically for asthma symptoms.

To date, there have not been any studies that have estimated the theoretically correct economic cost of health damages from wildfire smoke using primary data. There are two common approaches which can be used to calculate this WTP value: the contingent valuation method and the defensive behavior method. This study will apply the defensive behavior method to calculate the value of a reduction in health damages from smoke released by California's Station Fire of 2009 and compare this to a cost of illness estimate.

Defensive Behavior Method

The defensive behavior method, also referred to as the averting behavior method, is a revealed preference approach based on the health production function first outlined by Grossman (1972) with extensions to the model undertaken by Cropper (1981) and Harrington and Portney (1987). The framework of the model is based on the premise that an individual experiences some health output, such as a number of days spent sick which enters into his 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, defensive actions taken by the individual to decrease the chance he experiences a negative health outcome. Defensive actions are broken down into what are referred to as averting and mitigating actions, which are somewhat different. The former are actions taken to decrease the chance of being exposed to the pollutant that causes the negative health outcome, such as staying indoors or using an air cleaner in the home. 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. The sum of expenditures on mitigating activities and lost wages due to illness represents the cost of illness typically measured as the cost of health damages from wildfire smoke exposure.

This model can be used to calculate the individual 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 great detail in Dickie (2003) and Freeman (2003). Here we present a simple one period framework to set the stage for our empirical analysis. An individual produces some health output according to a health production function (also referred to as a symptom production function) as follows:

$$S = S(P, A, M, Z) \tag{2.1}$$

This health output S is a function of P which represents exposure to a pollutant, A represents averting activities that can be taken to reduce exposure to the pollutant or time spent sick, 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 demographics 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. This information can then be used to calculate the individual marginal value of reduced pollution equal to (see Freeman, 2003 for a full derivation):

$$-p_A\ [(\partial S/\partial P)\ /\ (\partial S/\partial A)] \tag{2.2a}$$

or

$$-p_M\ [(\partial S/\partial P)\ /\ (\partial S/\partial M)] \tag{2.2b}$$

The price of any averting or mitigating activity multiplied by the marginal rate of technical substitution between pollution and that averting or mitigating activity in producing a given number of sick days. The marginal value of reduced time spent sick equals:

$$-p_A\ /\ (\partial S/\partial A) \tag{2.3a}$$

or

$$-p_M\ /\ (\partial S/\partial M) \tag{2.3b}$$

The marginal willingness to pay 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. We will illustrate adaption of this model to wildfire smoke emissions by calculating the individual willingness to pay for a reduction in wildfire smoke induced symptom days. A simple cost of illness estimate will be compared to this marginal willingness to pay value to quantify the magnitude of underestimation. In addition, we will calculate the ratio of WTP: COI to contribute another ratio to the literature for others that may be able to measure the cost of illness but desire willingness to pay estimates.

III. THE STATION FIRE

Study Area

The Station Fire began on Wednesday, August 26, 2009 in the Angeles National Forest, located adjacent to the Los Angeles, California metropolitan area. The wildfire became extremely difficult to contain due to hot weather conditions, thick brush, as well as rugged and steep terrain faced by firefighters. By the time the Station fire was fully contained on October 16, 2009 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 residents in surrounding communities from their homes (InciWeb, 2009). During the Station Fire, a number of surrounding communities faced unhealthy air quality levels and were issued smoke advisory warnings by the South Coast Air Quality Management District and the Los Angeles County Department of Public Health. These warnings advised residents in all areas where smoke could be seen or smelled to avoid unnecessary outdoor activities, keep windows and doors closed and run the air conditioner. Sensitive populations such as those with heart or lung disease, the elderly and children were advised to stay indoors. The Station Fire provides a unique natural experiment to analyze health effects and defensive actions taken in response to the wildfire smoke for two reasons. First, it was the largest wildfire in Los Angeles County's modern history. Second, it occurred near one of the largest metropolitan areas in the United States. Wildfires rarely affect large urban populations given that they typically occur in rural areas (Vedal, 2006). Figure 2.1 is a NASA image of the location of the wildfire smoke taken mid-morning on August 30, 2009.

FIGURE 2.1
Smoke from the Station Fire

Image Credit: NASA/GSFC/LaRC/JPL, MISR Team

Data Collection

To gather data to implement this study, a survey was initially created in the summer of 2009 and focus groups were held in Anaheim, California during the same summer to pretest the survey. The survey was also reviewed by experts in the field of health economics. Approximately six weeks after the Station Fire began the survey was mailed to a random sample of one thousand residents in five cities in the vicinity of the Station Fire. These cities included Duarte, Monrovia, Sierra Madre, Burbank and Glendora, California. They 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 indeed impacted by the wildfire smoke (air quality monitoring stations are located within the cities of Burbank and Glendora, while the others have stations close by). The cities were also far enough away from the fire that it was unlikely residents' homes were damaged or destroyed, allowing survey respondents to focus on the health effects from the wildfire smoke rather than the damages from the fire itself. Resident contact information was obtained through Survey Sampling International. The first round of mail surveys included a cover letter explaining the purpose of the survey as well as a $1 bill attached to the front. A reminder postcard was then sent to all non-respondents followed by a second round of survey mailing.

Three hundred individuals who had not yet responded to either of these first two mailings were split into three groups of one hundred. The first group received a third survey by regular mail, the second group received a third survey by priority mail, and the final group received a third survey by regular mail in an envelope which also included one Ghirardelli Squares chocolate. Given the high cost of survey implementation, this was done as a means to test whether spending more money on incentives for survey respondents is worth the increased response rate. For the group that received the survey by regular mail, each survey cost $4.04 to mail, accounting for the cost of survey printing, stamps, and envelopes. There was a response rate of 12% from this group. Taking the total cost of this survey mailing divided by the number of surveys completed and returned, results in a cost per completed survey of $33.67. For the second group which received the survey by priority mail, each survey cost $7.30 and there was a response rate of 19%, resulting in a cost per completed survey of around $38.42. Finally, mailing the survey with chocolate to the third group cost $4.33 per survey and had a response rate of 16%, resulting in a cost per completed survey of around $27.06. While this represents a small sample, it indicates that incentives such as including a piece of chocolate in the survey envelope may be more cost-efficient than more expensive methods such as sending surveys by priority mail.

Including all three survey mailings, the initial sample size was one thousand individuals, forty surveys were not deliverable, and four hundred and fifty-eight complete surveys were returned for an overall response rate of 48%. After removing incomplete surveys and respondents who were not home during the fire, there remained a total of four hundred and thirteen usable surveys. The cover letter, survey, and reminder postcard can all be found in the 'Survey Instrument' section at the end of this dissertation.

To measure the type and severity of health effects experienced as a direct result of exposure to smoke and ash during the Station Fire, respondents were asked a series of questions. First, they were asked whether or not they experienced ear, nose or throat symptoms such as cough, sore throat, burning eyes, runny nose, sinus problems, etc.; breathing problems such as shortness of breath, aggravation of asthma, bronchitis or emphysema; heart problems such as rapid heartbeat or chest pain; or other symptoms such as anxiety, nausea, or dizziness. In addition, respondents were asked to report the total number of days symptoms were experienced as well as the level of pain experienced from all symptoms on a scale of 1-5.

To measure the mitigating actions respondents took as a direct result of these reported health effects, respondents were asked whether or not they went to a physician, urgent care, emergency room or hospital for symptoms, or took prescribed medications. They were also asked whether or not they took nonprescription medications or visited a non-traditional healthcare provider as a result of symptoms. Individuals were asked to report any monetary expenditures made on these mitigating actions, as well as the time spent in commuting and obtaining any medical care. In addition, individuals were asked whether or not they missed work or recreation days as a direct result of symptoms.

Averting activities can reduce health effects by decreasing exposure to the wildfire smoke. These activities include evacuating the area, covering the face with a mask, running the air conditioner more, using an air cleaner in the home, removing ashes from property, avoiding going to work, staying indoors and avoiding normal outdoor recreation activities. These activities were chosen based on focus groups, recommendations from the Centers for Disease Control and Prevention, the Environmental Protection Agency and the South Coast Air Quality Management District 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 individuals take when exposed to health risks from wildfire smoke (Mott et al., 2002; Kunzli et al., 2006). Individuals were asked to report the length of time averting actions were taken as a direct result of exposure to smoke from the Station Fire from a choice of never, 1-5 days, 6-10 days, and 11 or more days. Respondents were also asked to report their monetary expenditures on these activities where appropriate.

In regards to pollution concentrations, given recent findings that subjective, within-community pollution measures can be quite different from objective, community-wide measures from air quality monitoring stations (Kunzli et al., 2006), the survey first questioned respondents about whether or not they could smell smoke and/or ash both inside and outside their home during the fire and the weeks following. If they indicated that they could, they were asked to choose from a series of ranges the number of days they noticed the smell; 1-5 days, 6-10 days, 11-15 days, or more than 15 days.

Finally, respondents were asked a series of questions about exogenous factors which could affect their production of health or their decision to undertake defensive actions during the Station Fire. These include the respondent's health history, lifestyle factors and demographic information, as well as information obtained and beliefs about the effects of wildfire smoke on health, as recommended by Dickie (2003) and Freeman (2003). A description of all study variables and their sample statistics can be found in Table 2.1.

TABLE 2.1
Variable Definitions

Variable	Coding	Mean	Std. Dev.	Min	Max
Perceived Pollution Levels					
Days smoke smelled indoors	0=no days; 3=1-5 days; 8=6-10 days; 13=11-15 days; 16=more than 15 days	3.43	4.21	0	16
Smelled smoke indoors 1-5 days	1= yes, 0= no	0.33	0.47	0	1
Smelled smoke indoors > 5 days	1= yes, 0= no	0.24	0.43	0	1
Days smoke smelled outdoors	0=no days; 3=1-5 days; 8=6-10 days; 13=11-15 days; 16=more than 15 days	7.77	4.91	0	16
Smelled smoke outdoors 1-5 days	1= yes, 0= no	0.33	0.47	0	1
Smelled smoke outdoors > 5 days	1= yes, 0= no	0.62	0.49	0	1
Illness Information					
Symptom days	count	3.28	6.06	0	45
Level of pain from symptoms	scale of 1-5: 1=no pain or discomfort; 5=severe pain or discomfort	1.02	1.42	0	5
Ear, nose or throat symptoms	1= yes, 0= no	0.36	0.48	0	1
Breathing symptoms	1= yes, 0= no	0.18	0.39	0	1
Heart symptoms	1= yes, 0= no	0.04	0.20	0	1
Other symptoms	1= yes, 0= no	0.09	0.28	0	1
Mitigating Actions					
Doctor/prescription meds.	1= yes, 0= no	0.06	0.24	0	1
Non-prescription meds.	1= yes, 0= no	0.13	0.33	0	1
Non-traditional healthcare provider	1= yes, 0= no	0.01	0.11	0	1
Missed work	1= yes, 0= no	0.04	0.19	0	1
Missed recreation	1= yes, 0= no	0.28	0.45	0	1
Averting Actions					
Evacuated	1= yes, 0= no	0.06	0.23	0	1
Wore a face mask	1= yes, 0= no	0.07	0.26	0	1
Home air cleaner	1= yes, 0= no	0.21	0.41	0	1
Avoided going to work	1= yes, 0= no	0.05	0.21	0	1
Removed ashes from property	1= yes, 0= no	0.57	0.50	0	1
Ran the air conditioner more	1= yes, 0= no	0.60	0.49	0	1
Stayed indoors	1= yes, 0= no	0.73	0.44	0	1
Avoided normal outdoor recreation/exercise	1= yes, 0= no	0.78	0.42	0	1
Health History					
Current respiratory condition	1= yes, 0= no	0.12	0.32	0	1
Current heart condition	1= yes, 0= no	0.09	0.28	0	1
Experienced health effects from wildfire smoke in past	1= yes, 0= no	0.24	0.42	0	1
Health and Lifestyle					
Times per week of exercise	0=0 times/week; 1=1-2 times/week; 2=3-5 times/week; 3=more than 5 times/week	1.62	0.92	0	3
Smoker	1= yes, 0= no	0.08	0.28	0	2
Alcoholic drinks per week	0=none; 1=1-7 drinks/week; 2=8-14 drinks/week; 3=more than 14 drinks/week	0.60	0.73	0	3
Current health is excellent	1= yes, 0= no	0.29	0.45	0	1
Current health is good	1= yes, 0= no	0.55	0.50	0	1
Current health is fair	1= yes, 0= no	0.14	0.35	0	1
Current health is poor	1= yes, 0= no	0.02	0.14	0	1
Hours per week of indoor recreation	continuous	2.95	5.89	0	91
Hours per week of outdoor recreation	continuous	4.95	7.11	0	77
Has a regular doctor	1= yes, 0= no	0.89	0.31	0	1

TABLE 2.1
Variable Definitions, cont.

Variable	Coding	Mean	Std. Dev.	Min	Max
Demographics					
Male	1=male, 0=female	0.60	0.49	0	1
Married	1=yes, 0=no	0.69	0.46	0	1
Age	continuous	59.11	15.37	24	94
White	1=yes, 0=no	0.79	0.41	0	1
Graduate school graduate	1= yes, 0= no	0.20	0.40	0	1
College graduate	1= yes, 0= no	0.62	0.49	0	1
Employed full-time	1= yes, 0= no	0.48	0.50	0	1
Employed part-time	1= yes, 0= no	0.08	0.27	0	1
Not employed	1= yes, 0= no	0.42	0.49	0	1
Has health insurance	1=yes, o=no	0.92	0.27	0	1
Months at current zip code	continuous	258.66	184.96	7	816
Number of children under 18 years old in household	continuous	0.43	0.83	0	4
Lives in Duarte	1= yes, 0= no	0.13	0.34	0	1
Lives in Monrovia	1= yes, 0= no	0.20	0.40	0	1
Lives in Sierra Madre	1= yes, 0= no	0.08	0.26	0	1
Lives in Burbank	1= yes, 0= no	0.19	0.40	0	1
Lives in Glendora	1= yes, 0= no	0.40	0.49	0	1
Income	15= < 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= > 200,000	83.52	53.50	15	200
Beliefs					
Heard or read about possible health effects	1= yes, 0= no	0.86	0.35	0	1
Believes smoke can affect health	1= yes, 0= no	0.90	0.31	0	1
Believes that averting actions were very or somewhat effective at reducing symptoms from smoke	1= yes, 0= no	0.46	0.50	0	1

Pollution Levels

While wildfire smoke is made up of a number of pollutants, particulate matter poses the most serious threat to human health from short-term exposure (Lipsett et al., 2008). According to the U.S. Environmental Protection Agency, problematic particles are those that are ten micrometers in diameter and smaller because these can easily enter the lungs and cause serious health impacts. Wildfire smoke contains particles which are 2.5 micrometers in diameter and smaller, referred to as PM2.5, as well as particles which are 10 micrometers in diameter and smaller, referred to as PM10 (U.S. EPA, Particulate Matter). Exposure to low levels of carbon monoxide (CO) released during a wildfire can cause fatigue in healthy individuals and more serious health effects such as chest pain in individuals with preexisting heart conditions (U.S. EPA, Indoor Air Quality).

Data on concentrations of particulate matter and carbon monoxide released during the Station Fire were taken from the California Environmental Protection Agency Air Resources Board. Of the five cities surveyed for the study, Burbank and Glendora are the only two which have air quality monitoring stations within city limits, while the others have stations close by. Data on PM2.5 concentrations during the weeks the wildfire burned were available for the cities of Burbank and Glendora, while data on PM10 concentrations were available for the city of Glendora only. Data on carbon monoxide (CO) were directly available from monitoring stations in Burbank and Glendora. While there are no monitoring stations in Duarte, Monrovia or Sierra Madre, there are stations very close by which reported levels of CO during the weeks the Station Fire burned. CO concentrations from the Azusa monitoring station were used as a proxy for levels in Duarte and Monrovia, as the station is located four miles from the former and six miles from the latter. CO concentrations from the Pasadena monitoring station were used as a proxy for levels in Sierra Madre, as these cities are located six and a half miles apart.

Table 2.2 presents six-day averages of daily maximum and daily average concentrations of PM2.5, PM10 and CO where data were available, as well as the number and percentage of survey respondents in each surveyed city who smelled smoke both inside and outside of their home for a given range of days.

TABLE 2.2
Objective and Subjective Pollution Levels during the Station Fire

	CO (ppm)		*PM2.5 (μg/m3)*		*PM10 (μg/m3)*		*Smelled Smoke Inside of Home*					*Smelled Smoke Outside of Home*				
	average (6-d mean)	peak (6-d mean)	average (6-d mean)	peak (6-d mean)	average (6-d mean)	peak (6-d mean)	None	1-5 days	6-10 days	11-15 days	> 15 days	None	1-5 days	6-10 days	11-15 days	> 15 days
City																
Duarte (n=54)	0.68	1.4					18 (33%)	20 (37%)	8 (15%)	5 (9%)	3 (6%)	2 (4%)	15 (28%)	13 (24%)	10 (19%)	14 (26%)
Monrovia (n=84)	0.68	1.4					29 (35%)	29 (35%)	16 (19%)	7 (8%)	3 (4%)	2 (2%)	24 (29%)	32 (38%)	14 (17%)	12 (14%)
Sierra Madre (n=31)	0.48	1.8					16 (52%)	9 (29%)	6 (19%)	0 (0%)	0 (0%)	3 (10%)	9 (29%)	11 (35%)	3 (10%)	5 (16%)
Burbank (n=80)	0.64	1.57	25.18	93.5			37 (46%)	24 (30%)	15 (19%)	3 (4%)	1 (1%)	4 (5%)	28 (35%)	24 (30%)	13 (16%)	11 (14%)
Glendora (n=164)	0.65	1.42	46.83	120.83	53.82	133.12	75 (46%)	56 (34%)	21 (13%)	8 (5%)	4 (2%)	11 (7%)	61 (37%)	53 (32%)	27 (16%)	12 (7%)

During the Station Fire, daily average levels of PM2.5 reached as high as 82.9 $\mu g/m^3$ in Glendora and 38 $\mu g/m^3$ in Burbank, and exceeded national standards of 35 $\mu g/m^3$ for three days in Glendora and one day in Burbank during the first week the fire burned. Daily peak one hour concentrations of PM2.5 were as high as 223 $\mu g/m^3$ in Glendora and 189 $\mu g/m^3$ in Burbank. Daily average concentrations of PM10 reached 93.8 $\mu g/m^3$ in Glendora and one hour peak concentrations reached 214.4 $\mu g/m^3$. These elevated levels of particulate matter are very similar to estimates reported for other large wildfires. During Colorado's Hayman fire of 2002, Sutherland et al. (2005) reported a 24-hour mean PM2.5 concentration of 63.1 $\mu g/m^3$ during two spike days following the wildfire. For the same wildfire, Vedal and Dutton (2006) reported 24-hour mean concentrations of PM2.5 of 44-48 $\mu g/m^3$ and peak one hour concentrations of 200 $\mu g/m^3$. Wu et al. (2006) estimated PM2.5 concentrations of 75-90 $\mu g/m^3$ during the 2003 Southern California wildfires.

Figure 2.2 shows daily average and daily maximum levels of PM 2.5 and CO in the cities of Glendora and Burbank during the two weeks following the start of the Station Fire. Approximately one week after the fire began all five of the cities surveyed for this study were warned that air quality levels would likely reach unhealthy levels by the South Coast Air Quality Management District.

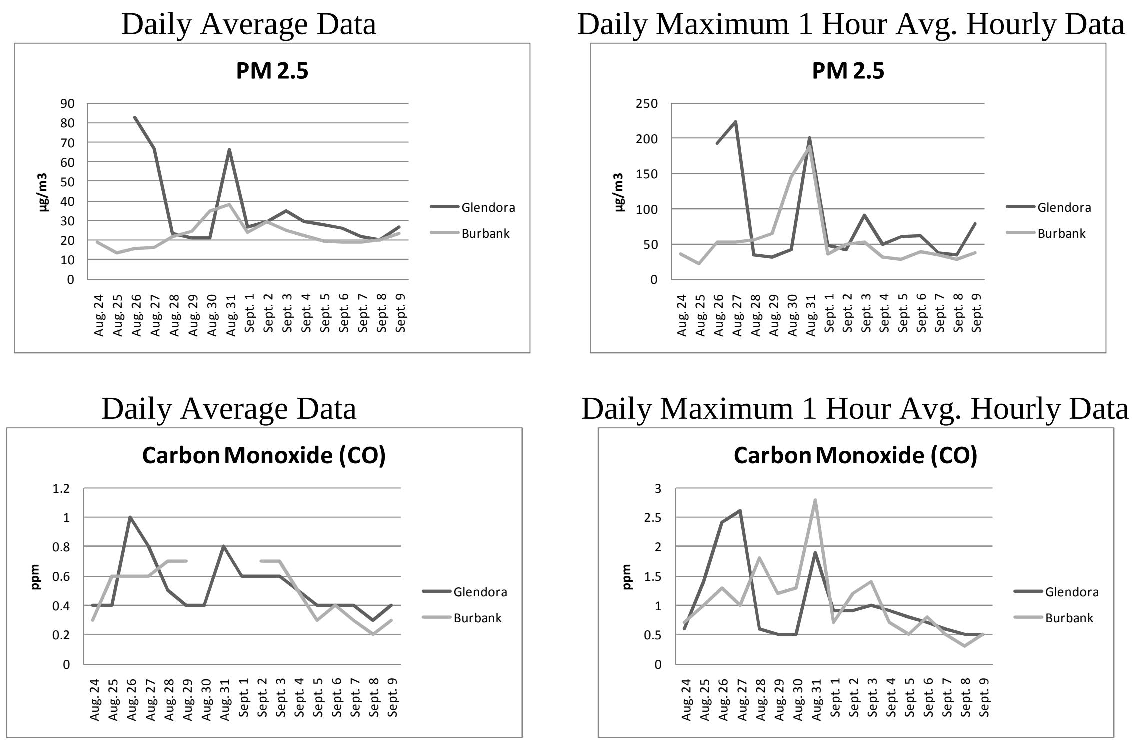

FIGURE 2.2
Concentration of PM2.5 and CO in Glendora and Burbank – 8/24-9/9, 2009

Data retrieved from: CA EPA Air Resources Board, Air Quality Data Query Tool.
http://www.arb.ca.gov/aqmis2/aqdselect.php

Health Effects

Of the 413 survey respondents, 156 experienced at least one symptom from exposure to the Station Fire smoke. Of these 156 individuals who experienced symptoms, the average length of time symptoms lasted was for 8.7 days. The Centers for Disease Control and Prevention and U.S. Environmental Protection Agency report that individuals with heart or lung disease are at greater risk for experiencing health effects from wildfire smoke. Table 2.3 outlines the number and percentage of all 413 survey respondents who experienced each type of health symptom, as well as the number and percentage of those individuals both with and without a preexisting heart or respiratory condition who experienced each type of symptom.

TABLE 2.3
Health Symptoms of Survey Respondents

	All Respondents (n=413)	*Preexisting Condition (n=77)*	*No Preexisting Condition (n=336)*
At least one symptom	156 (38%)	47 (61%)	109 (32%)
Ear, nose or throat symptoms	147 (36%)	43 (56%)	104 (31%)
Breathing symptoms	76 (18%)	30 (39%)	46 (14%)
Heart symptoms	18 (4%)	7 (9%)	11 (3%)
Other symptoms (anxiety, nausea, etc.)	36 (9%)	12 (16%)	24 (7%)

Averting and Mitigating Actions

The defensive, or averting, behavior method is based on the assumption that individuals respond to threats of pollution and other environmental contaminants by taking defensive actions. If this information is to be used to calculate the economic value of a reduction in an environmental contaminant, a few assumptions underlying the method should be confirmed in the data. First, individuals need to believe that the pollutant at hand can affect their health in order for them to choose to invest time and money in taking actions to defend themselves against exposure. Second, we need to know if the majority of individuals are actually taking these defensive actions in response to exposure (Dickie, 2003; Freeman, 2003) and that they believe these actions are effective (Freeman, 2003).

Results of the Station Fire survey show that 90% of all survey respondents believe that exposure to wildfire smoke can affect a person's health and 89% reported taking some defensive action as a direct result of exposure to the wildfire smoke. Of these respondents who took at least one action, 77% thought they were at least a little effective at reducing or eliminating the health effects from exposure, 4% thought they were not effective at all, and the rest reported that they did not know the effectiveness of the actions taken.

Dickie (2003) summarizes defensive behavior method studies and finds that 15-98% of survey respondents take defensive actions in response to an environmental contaminant, with the majority reporting somewhere in the middle. We feel that our finding of 89% represents a high enough percentage of survey respondents to be able to accurately apply the defensive behavior method. Table 2.4 outlines the number and percentage of survey respondents who reported taking each averting or mitigating action, along with the average cost reported by those who took that action. Four respondents reported averting expenditures well above the mean, so any expenditure from these four respondents greater than 3 standard deviations from the sample mean was re-coded to the highest value without the outlier. Table 2.4 with these outliers not recoded can be found in the Appendix, Table 2.A.

TABLE 2.4
Averting and Mitigating Actions Taken by Respondents and Average Expenditure on Each (n=413)

Averting Actions	*Number of Survey Respondents*	*Percentage of Survey Respondents*	*Average Expenditure*
Evacuated	23	5.6%	$257.95
Wore a mask	29	7.0%	$6.04
Used an air cleaner, filter or humidifier	88	21.3%	$26.93
Avoided going to work	19	4.6%	$219.41[2]
Removed ashes from property	237	57.4%	$8.67
Ran air conditioner more than usual	249	60.3%	$27.66[3]
Stayed indoors more than usual	302	73.1%	N/A
Avoided normal outdoor recreation/exercise	321	77.7%	N/A
Mitigating Actions			
Obtained medical care/prescription medications	26	6.3%	$77.87[4]
Took non-prescription medicines	52	12.6%	$16.86
Went to non-traditional healthcare provider	5	1.2%	$33.00
Missed work	15	3.6%	$691.76
Lost days of recreation activities	114	27.6%	NA

[2] Lost earnings reported by respondent.

[3] Respondents were not asked to report this cost. The price was calculated as the kilowatt hours per day used in running the air conditioner*the cost per kilowatt hour*the average number of days respondents took this averting action. According to the California Energy Commission, the average California resident uses 27 kilowatt hours to run their central air conditioning for 12 hours/day (assuming the air conditioner is run for 120 days of the year). According to the U.S. Energy Information Administration, residents in California in September of 2009 were charged 15.76 cents per kilowatt hour used. Respondents who ran the air conditioning more as a result of the wildfire smoke ran it for an average of 6.5 days. This results in a value of $27.66.

[4] Includes the opportunity cost of time spent traveling to and receiving medical care, calculated as the number of hours spent in these activities*the hourly wage rate reported by that respondent.

IV. MAXIMUM SIMULATED LIKELIHOOD ESTIMATION OF A HEALTH PRODUCTION FUNCTION

To calculate the full economic cost of the health effects from exposure to the smoke from the Station Fire, a health production function such as that outlined in equation (2.1) is estimated using regression analysis. The number of symptom days experienced by survey respondents is the dependent variable of interest, regressed on the independent variables that would be expected to influence this. This includes everything on the right hand side of the health production function, including pollution levels, averting and mitigating actions, the individual's health history, lifestyle factors and demographic factors.

Previous findings show that averting and mitigating action variables are often jointly determined with health outcomes and correcting for this endogeneity is important for consistent estimation of regression parameters (Joyce et al., 1989; Alberini et al., 1996; Dickie, 2005). The endogeneity typically arises due to correlation between unobserved factors that affect both the health outcome as well as the choice of averting and mitigating actions (Dickie, 2003). A typical solution to the endogeneity problem is to employ an instrumental variables approach, such as two-stage least squares. However, given that the dependent variable in our analysis is a count variable (the number of symptom days experienced) and the potentially endogenous averting and mitigating action variables are binary (whether or not the action was undertaken), simple two-stage approaches will not provide consistent estimators (Wooldridge, 2002; Terza et al., 2008; Staub, 2009). To control for potential endogeneity in this nonlinear framework, we apply a maximum simulated likelihood estimation model developed by Partha Deb and Pravin

Trivedi.[5] Following Deb and Trivedi (2006a,b) the model has the following equations for the health outcome and the endogenous binary regressor:

$$Pr\ [Y_i = y_i \mid x_i, d_i, l_i] = f\ (x_i'\beta + \gamma d_i + \lambda l_i) \qquad (2.4)$$

$$Pr\ [d_i = 1 \mid z_i, l_i] = g\ (z_i'\alpha + \delta l_i) \qquad (2.5)$$

For our purposes, in the outcome equation (2.4), y_i represents the total number of days symptoms from the wildfire smoke were experienced and x_i represents a vector of exogenous variables influencing symptom days, such as objective or perceived pollution levels, type of symptom experienced, health history, demographics and lifestyle factors, with associated parameters β. These represent the exogenous variables that have been found to influence an individual's health outcome (see Dickie, 2003; Freeman, 2003). Higher actual or perceived pollution levels are expected to result in a greater number of expected symptom days, all else constant. Individuals with chronic health conditions or a less healthy lifestyle overall are expected to have more symptom days. It is uncertain what effect type of symptom experienced and various demographic factors will have on expected symptom days. The potentially endogenous binary regressor (i.e. averting and mitigating actions) is represented by d_i, with associated parameter γ. These variables are expected to have a negative effect on expected symptom days. The error term in each equation is partitioned into a vector of latent factors l_i and an independently distributed random error term. The latent factors represent unobserved individual specific characteristics which affect both the choice of averting/mitigating actions as well as the health outcome. They have associated parameters λ in the health outcome equation, referred to as factor loadings.

[5] We graciously thank Partha Deb for providing access to his Stata program treatreg2.

In equation (2.5), which models the binary endogenous regressor, z_i represents a vector of exogenous variables which could affect the use of the endogenous averting or mitigating action variable, with associated parameters α. These could be pollution levels, type of symptom experienced, health history, demographics, lifestyle factors, as well as beliefs about the effects of wildfire smoke on health. Higher pollution levels are expected to have a positive effect on the probability of undertaking a given averting or mitigating activity, as are beliefs that wildfire smoke can affect human health. It is uncertain what the effect of other variables will be. Equations (2.4) and (2.5) can contain the exact same set of exogenous variables, however, for more robust identification, instrumental variables which are included in the binary endogenous variable equation but excluded from the outcome equation can be used. Again, the error term is partitioned into latent factors l_i with associated parameters δ and an independently distributed random error term.

The observed random outcome variable y_i and the observed endogenous treatment variable d_i are modeled using appropriate distribution functions f (for a count variable) and g (for a binary variable). Following Deb and Trivedi (2006a,b), the joint distribution of the health outcome and binary endogenous variable, conditional on common latent factors, can then be specified as follows:

$$Pr\,[Y_i = y_i, d_i = 1 \mid x_i, z_i, l_i] = f\,(x_i'\beta + \gamma d_i + \lambda l_i) * g\,(z_i'\alpha + \delta l_i) \tag{2.6}$$

Although the latent factors l_i are unknown, it is assumed that their distribution is known and can be integrated out of the joint density. The method of maximum simulated likelihood (Gourieroux et al., 1984) is then applied to evaluate the integral. The latent factors are estimated by taking a certain number of draws of a pseudo-random number from an assumed standard normal distribution. The estimator then maximizes the average simulated log likelihood function, which is equivalent to maximizing the log-likelihood function if enough simulation draws are used.

V. RESULTS

To calculate the full economic cost of the health effects from exposure to the smoke from the Station Fire using equation (2.3a) or (2.3b), the researcher needs to estimate the marginal effect of any averting or mitigating action on expected symptom days, along with the full cost of this action. Preliminary analyses indicate that "Home air cleaner" is the only endogenous averting or mitigating action variable and the only variable that has a negative and statistically significant effect on expected symptom days.[6] As a result, this variable is focused on in the maximum simulated likelihood estimation and used to calculate equation (2.3a). Air cleaners and purifiers are recommended and often used in the home during wildfires to help reduce indoor particle levels (Lipsett et al., 2008; U.S. EPA, Indoor Air Quality) and this is the case for the 21% of survey respondents who used an air cleaner to prevent health damages from the Station Fire smoke. Results from the maximum simulated likelihood regression model of symptom days, including only those variables which had a statistically significant effect on expected symptom days, can be found in Table 2.5.

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[6] A version of the Hausman specification error test is used to test for endogeneity of the averting and mitigating action variables in the health production function equation. See Hausman, 1976 and Gujarati, 2003. Preliminary analysis shows that only three averting actions, "Home air cleaner", "Ran the air conditioner more", and "Avoided normal outdoor recreation/exercise" could be explained by an appropriate set of instrumental variables, which is a required feature to employ this test. These instrumental variables include "Employed full-time," "Months at current zip code," "Income", and "Believes smoke can affect health."

TABLE 2.5
Defensive Behavior Model

Variable	*Coefficient*	*Robust Std. Error*
SYMPTOM DAYS - Negative Binomial Regression		
Smelled smoke indoors > 5 days	0.394***	0.142
Smelled smoke outdoors > 5 days	0.953***	0.168
Ear, nose or throat symptoms	3.630***	0.232
Breathing symptoms	0.789***	0.183
Other symptoms	0.719***	0.221
Home air cleaner	-0.848***	0.163
Hours per week of outdoor recreation	-0.023*	0.012
Male	-0.341**	0.151
Married	-0.345**	0.153
Age	0.012**	0.005
College graduate	0.479***	0.141
Employed part-time	0.625**	0.305
Lives in Duarte	0.539**	0.225
Lives in Burbank	0.460**	0.185
Lives in Glendora	0.406**	0.174
Constant	-3.701***	0.476
HOME AIR CLEANER - Probit Regression		
Smell smoke inside > 5 days	0.362	0.259
Smell smoke outside > 5 days	0.336	0.282
Ear, nose or throat symptoms	0.672***	0.242
Breathing symptoms	0.168	0.265
Other symptoms	1.374***	0.333
Hours per week of outdoor recreation	-0.017	0.021
Male	-0.183	0.246
Married	0.437	0.268
Age	-0.006	0.010
College graduate	0.375	0.248
Income	-0.005**	0.003
Employed full-time	0.560**	0.284
Employed part-time	0.519	0.461
Lives in Duarte	-0.220	0.400
Lives in Burbank	0.411	0.307
Lives in Glendora	0.496*	0.272
Believes smoke can affect health	1.426**	0.703
Constant	-3.481***	1.096
/lambda	0.858***	0.072
/lnalpha	-13.657***	2.491
N =	377	
Log Likelihood =	-672.066	
Wald chi2 (24) =	424.71	
Prob > chi2 =	0.0000001	

*: p<0.10, **: p<0.05, ***: p<0.01

Expected symptom days were modeled with a negative binomial count data distribution and the endogenous binary treatment variable, "Home air cleaner," was assumed to follow a normal distribution. Two thousand simulation draws were used based on recommendations from Deb and Trivedi (2006a) and robust standard errors which take simulation error into account are reported.

Determinants of Expected Symptom Days

The results of the regression model in Table 2.5 show that respondents who smelled smoke inside or outside the home for greater than five days were more likely to experience a greater number of symptom days, holding all other variables constant. Similarly, Kunzli et al. (2006) found that the number of days wildfire smoke was smelled indoors was an important determinant of health effects from the 2003 Southern California wildfires. We initially included actual pollution levels in the model, however, similar to findings by Kunzli et al. (2006) these were not found to have a significant effect on expected symptom days. 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 experienced, compared to heart symptoms. In addition, using an air cleaner has a negative and statistically significant effect on the expected number of symptom days experienced. This supports previous findings. Mott et al. (2002) also found that greater use of high-efficiency air cleaners in the home was associated with reduced odds of reporting adverse health effects during a 1999 wildfire.

Similarly, Mott et al. (2002) found that during a 1999 wildfire in northern California, greater use of high-efficiency air cleaners in the home was associated with reduced odds of reporting adverse health effects. This beneficial effect of using air cleaners during wildfire events is further supported by a study which took place throughout Colorado during the 2002 wildfire season by Henderson et al., 2005. The authors conducted a study on the effectiveness of air cleaners during wildfires and prescribed burns and found that homes with air cleaners experienced 63-88% less particulate matter in their home than those without air cleaners. A variety of health, lifestyle and demographic factors also have a significant effect on the expected number of symptom days.

Determinants of Air Cleaner Use

All variables included in the symptom production function, as well as any additional explanatory variables which may influence the use of a home air cleaner, were included in the probit model for the endogenous averting action variable "Home air cleaner." The discussion here will be limited to those variables which had a statistically significant effect on the use of an air cleaner. If the respondent experienced ear, nose or throat symptoms or other symptoms such as nausea or anxiety, this has a positive effect on the probability of using an air cleaner, compared to other types of symptoms. Higher income levels are associated with a decreased probability of using an air cleaner in the home. This runs contrary to previous findings that higher income levels are associated with an increased probability of taking averting actions (Akerman et al., 1991; Smith et al., 1995; Abrahams et al., 2000; Um et al., 2002). In addition, individuals who believe that smoke can affect a person's health were more likely to use an air cleaner in the home to minimize exposure to the smoke, all else constant.

Finally, the positive and significant coefficient on the latent factor, lambda, suggests that individuals who are more likely to use an air cleaner, based on unobserved characteristics, are more likely to experience symptom days. This could reflect some predisposition to getting sick. For instance, individuals who are more likely to experience symptoms from smoke may realize this, and as a result they may be more likely to take averting actions, such as using an air cleaner in their home during a wildfire.

WTP for a Reduction in One Wildfire Smoke Induced Symptom Day

Given that using a home air cleaner has a negative and statistically significant effect on expected symptom days and an observable cost, this is the averting action used to calculate the individual willingness to pay for a decrease in symptom days from wildfire smoke. The incremental effect of this endogenous input on output is -0.31, meaning the use of an air cleaner is expected to reduce symptom days by 0.31.[7] Taking the average of the cost reported by those respondents who used an air cleaner during the Station Fire and reported a cost (including zero) results in an estimated price of $26.93 for this averting action. From equation (2.3a) the average respondent's marginal value of a reduction in one symptom day from exposure to wildfire smoke is equal to -$26.93/-0.31 = $86.87. This result falls within the range for avoiding one day of various symptoms found in the literature. For example, by combining a meta-analysis of

[7] The discrete change in expected count outcome resulting from a change in binary variable X^k from 0 to 1 can be calculated as: $[\mu_i|X^k=0][\exp(\beta^k)-1]$ where $\mu=\exp(X\beta)$, with all variables except X^k set at their sample mean.

morbidity valuation studies with a health status index, Johnson et al. (1997) estimated values ranging from $36-$68 to avoid one day of mild cough, $110 to avoid one day of shortness of breath, and $91-$129 to avoid one day of severe asthma.[8]

Including the full sample of respondents, an average of 3.3 symptom days were experienced. For the 38% of respondents who reported experiencing symptoms, an average of 8.7 symptom days were reported. This marginal value of reduced illness includes avoidance of the full cost of medical care and medications, lost wages from being unable to work, expenditures on preventative actions taken to avoid exposure to the smoke, as well as the disutility associated with symptoms or lost leisure.

Cost of Illness

A simple cost of illness for one symptom day was calculated using a formula from Alberini and Krupnick (2000). First, probit regression models are estimated for four mitigating actions: visiting a doctor or taking prescribed medications, taking nonprescription medications, missing work, and losing days of recreation activities.[9] In each model the dependent variable is coded with a 1 if the action was taken and 0 otherwise. Results of these full regression models can be found in the Appendix, Table 2.B. After removing variables that were not significant at standard significance levels, the models are re-estimated. For each action, the predicted probability that the action is taken, with independent variables set at their mean and symptom days set at 1, is multiplied by its average in-sample cost. These are the same average costs reported in

[8] All estimates were converted to 2009 U.S. dollars using the Consumer Price Index.

[9] Due to the fact that only five individuals went to a non-traditional healthcare provider, a regression model was not estimated for this mitigating action.

Table 2.4 except for work days lost, which is adjusted to represent the lost wages from one work day lost due to illness. Summing costs across all actions results in a cost of illness for one symptom day of $9.32.

The willingness to pay estimate of $86.87 exceeds this in-sample cost of illness estimate by a factor of about nine. This ratio is larger than that found in some previous studies of health damages which compare the two estimates but smaller than others. For instance, Rowe and Chestnut (1985) estimated a WTP: COI ratio ranging from 1.6-3.7 for asthma symptoms due to ozone exposure. Alberini and Krupnick (2000) estimated a WTP: COI ratio ranging from 1.61-2.26 for symptoms associated with various levels of air quality in Taiwan. However, Berger et al. (1987) found much greater differences when comparing willingness to pay and cost of illness estimates for seven light health symptoms. Mean daily willingness to pay values to avoid one day of various symptoms were always found to exceed daily cost of illness estimates, but the difference ranged from willingness to pay estimates about three times larger than cost of illness estimates to about thirty times larger, depending on the health symptom.

Our WTP: COI ratio of about nine raises some interesting points as this ratio has never been calculated for the specific case of health damages from wildfire smoke exposure. While 156 of the 413 respondents in this study experienced symptoms from smoke from the Station Fire, only 15 sought medical attention and an additional 11 took prescription medications. This suggests that overall health effects were relatively minor and the majority of individuals who experienced health symptoms did not require medical attention with a high associated cost. However, our results do show that of those 156 respondents who experienced health symptoms, 110 of them missed recreation days as a result of these symptoms. This suggests that the disutility associated with symptoms or lost leisure captured in the WTP estimate but not the COI estimate may be substantial for individuals exposed to wildfire smoke. In addition, 366 individuals in our sample took some preventative, averting action to minimize their exposure to smoke from the Station Fire, and these actions were costly.

The cost of illness is an underestimate of the economic cost of health effects from exposure to a pollutant because it ignores the value of averting expenditures as well as the disutility associated with symptoms or lost leisure that results from illness (Freeman, 2003). Our results support this finding and indicate that these two components of the economic cost of health damages from exposure to wildfire smoke are substantial.

VI. IMPLICATIONS

While there is a growing literature citing the need to incorporate the cost of damages to human health from exposure to wildfire smoke in assessments of the damages caused by wildfires, there is a lack of literature available to policy makers to assist them in obtaining these costs. In areas such as California where wildfires are prevalent and suppression costs are high, policy makers will continue to have to make informed decisions about the appropriate level of investment in future fire management and prevention practices. If these practices are to be evaluated on an economic efficiency based criterion, it is important to follow past recommendations of Gorte and Gorte (1979) as well as Butry et al. (2001) and include more than just suppression costs and insured losses in damage assessments of wildfires. Any proactive, consistent and thorough evaluation of fire management policies needs to focus on inclusion of all associated economic costs and benefits of a given wildfire.

This study used unique primary data during one of California's largest wildfires to date to explore the health damages experienced during the Station Fire of 2009 along with all associated economic costs. We confirm that concentrations of particulate matter and carbon monoxide were elevated in the cities surveyed during the Station Fire and find that 38% of survey respondents experienced at least one symptom as a result of exposure to the wildfire smoke. The majority of survey respondents indicated that they are aware that wildfire smoke can be damaging to their health, which is evident given that 89% made some expenditure of time or money in taking preventative actions to decrease their exposure to smoke from the Station Fire.

Estimation of a health production function reveals that the number of symptom days experienced was influenced by factors such as the number of days wildfire smoke was smelled outside of the home, demographic factors such as age, sex and marital status, as well as the use of a home air cleaner. This finding that increased use of air cleaners in the home is associated with reduced adverse health effects from wildfire smoke is consistent with findings by Mott et al. (2002) and Henderson et al. (2005) and provides additional support to suggestions by Henderson et al. (2005) that agencies may want to change recommendations during wildfires by advising individuals to use home air cleaners to avoid health damages from nearby wildfires rather that just staying indoors.

In terms of the cost of damages to health from the Station Fire smoke, we calculate a simple daily cost of illness estimate of $9.32. While policy makers may be comfortable using methods such as this due to the observable nature of medical expenditure data, it is widely understood that this method will underestimate the true economic cost of damages to human health. Applying the defensive behavior method reveals that individuals exposed to wildfire smoke during the Station Fire were willing to pay on average $86.87 to avoid one day of wildfire smoke induced symptoms. The discrepancy between the cost of illness and willingness to pay estimates confirm theoretical predictions that averting expenditures and the disutility associated with symptoms or lost leisure account for a large part of the economic cost of health damages from wildfire smoke.

While this is the first study to apply the defensive behavior method to the specific application of wildfire smoke exposure, we feel that it is a viable option to be used for calculating the economic cost of health damages from exposure to wildfire smoke to be included in damage assessments. Although this method is not flawless and concerns have been raised over issues such as joint production which are beyond the scope of this paper (see Bartik, 1988; Bresnahan and Dickie, 1994; Dickie, 2003), the framework provides an economically consistent approach to calculating a comprehensive estimate of this cost. This is beneficial for a number of reasons. First, while a handful of studies valuing health damages from wildfire smoke have attempted to transfer willingness to pay estimates from other studies or adjust cost of illness estimates into comprehensive willingness to pay estimates using assumed ratios, none of the willingness to pay estimates or calibration factors were originally estimated for the health damages associated with wildfires specifically. This study calculates both measures and estimates a WTP: COI ratio of nine. These findings reveal that a higher calibration factor may be warranted for the case of wildfire smoke. Second, while time and money constraints may make it difficult for agencies to collect primary data to undertake the defensive behavior method after each wildfire, the more estimates there are available in the literature, the easier it will be to accurately apply benefit transfer techniques and include all relevant costs of a given wildfire in damage assessments.

APPENDIX

TABLE 2.A
Averting and Mitigating Actions Taken by Respondents and Average Expenditure on Each with Outliers Included (n=413)

Averting Actions	***Number of Survey Respondents***	***Percentage of Survey Respondents***	***Average Expenditure***
Evacuated	23	5.6%	$471.59
Wore a mask	29	7.0%	$16.04
Used an air cleaner, filter or humidifier	88	21.3%	$36.19
Avoided going to work	19	4.6%	$390.00
Removed ashes from property	237	57.2%	$18.91
Ran air conditioner more than usual	249	60.1%	$27.66
Stayed indoors more than usual	302	72.9%	N/A
Avoided normal outdoor recreation/exercise	321	77.5%	N/A
Mitigating Actions			
Obtained medical care/prescription medications	23	5.6%	$77.87
Took non-prescription medicines	51	12.3%	$16.86
Went to non-traditional health provider	5	1.2%	$33.00
Missed work	14	3.4%	$691.76
Lost days of recreation activities	114	27.5%	NA

TABLE 2.B
Determinants of Mitigating Activities (Probit)[10]

	Doctor/Prescription Meds.		Non-prescription Meds.		Missed Work		Missed Recreation	
Variable	*Coeff.*	*Std. Error*	*Coeff.*	*Std. Error*	*Coeff.*	*Std. Error*	*Coeff.*	*Std. Error*
Days smoke smelled indoors								
1-5 DAYS	-0.103	0.437	**0.457***	0.278	1.229	0.929	**0.412***	0.224
6-10 DAYS	-0.596	0.575	0.475	0.337	**1.775***	0.972	**0.544****	0.276
11-15 DAYS	0.958	0.694	-0.157	0.565	1.353	1.231	**0.701***	0.418
> 15 DAYS	(empty)		**1.512****	0.592	(empty)		-0.109	0.524
Average daily maximum CO concentration	-1.155	2.111	-0.515	1.296	0.946	2.081	0.675	0.972
Symptom days	**0.136*****	0.032	**0.064*****	0.017	0.041	0.037	**0.132*****	0.020
Current respiratory condition	**0.798***	0.408	-0.404	0.321	-0.861	0.742	0.305	0.283
Current heart condition	-0.530	0.854	-0.577	0.512	1.027	1.003	-0.466	0.379
Experienced health effects from wildfire smoke in past	-0.236	0.448	**0.757*****	0.258	0.684	0.672	**0.821*****	0.225
Times per week of exercise	0.019	0.234	-0.108	0.148	0.585	0.388	**0.246****	0.121
Smoker	0.937	0.648	-1.172	0.888	0.498	0.993	0.550	0.339
Alcoholic drinks per week	-0.120	0.317	0.194	0.170	-0.119	0.435	0.157	0.135
Current health is excellent	-1.834	1.241	-1.038	0.917	3.671	327.915	-0.037	1.179
Current health is good	-1.828	1.202	-1.039	0.887	3.774	327.915	-0.189	1.160
Current health is fair	**-1.906***	1.149	-0.867	0.869	(omitted)		0.295	1.155
Hours per week of indoor recreation	0.021	0.052	0.020	0.030	**-0.322****	0.164	0.011	0.028
Hours per week of outdoor recreation	-0.048	0.041	0.018	0.023	0.020	0.055	-0.012	0.020
Has a regular doctor	(omitted)		0.033	0.376	-0.557	0.695	0.216	0.325
Male	**-1.452*****	0.512	**-0.542****	0.260	**-1.619****	0.655	-0.288	0.215
Married	**1.208****	0.521	-0.081	0.274	0.673	0.725	**0.547****	0.247
Age	-0.006	0.016	-0.008	0.010	-0.010	0.026	**-0.021****	0.009
White	-0.342	0.464	-0.046	0.304	**-1.120***	0.665	-0.187	0.263
Graduate school graduate	0.174	0.499	-0.172	0.293	0.567	0.542	**0.553****	0.261
College graduate	0.183	0.404	0.264	0.265	1.048	0.803	0.017	0.226
Employed full-time	-0.088	0.526	0.301	0.324	1.073	0.739	0.078	0.275
Employed part-time	0.074	0.733	-0.827	0.617	0.332	1.024	0.195	0.389
Has health insurance	0.500	0.773	0.537	0.495	-0.039	0.985	-0.639	0.394
Lives in Duarte	-0.264	0.631	-0.415	0.449	(omitted)		**-0.597***	0.339
Lives in Monrovia	0.033	0.476	0.150	0.301	0.191	0.637	0.372	0.268
Lives in Burbank	0.165	0.483	0.131	0.307	(omitted)		-0.125	0.257
Income	-0.006	0.005	0.000	0.003	0.000	0.006	-0.002	0.002
Heard or read about possible health effects	0.356	0.625	-0.340	0.312	0.482	0.852	-0.207	0.274
Believes smoke can affect health	(omitted)		(omitted)		(omitted)		0.179	0.411
Constant	1.124	3.477	0.020	2.280	-8.732	327.951	-1.586	1.972
N =	287		339		187		373	
Log Likelihood	-43.666		-94.202		-27.330		-130.874	
LR chi2	82.460		91.690		44.840		190.690	
Prob > chi2	0.000001		0.000001		0.022900		0.000001	

*: p≤0.10, **: p≤0.05, ***: p≤0.01

[10] A two-stage residual inclusion approach is used to test the endogeneity of 'Symptom days' in each mitigating action model. This results in a failure to reject the null hypothesis of exogeneity of this variable in each model.

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CHAPTER THREE

A Comparison of Defensive Expenditures and Willingness to Pay for Wildfire Smoke Reduction: How Different are These Two Methods?

I. INTRODUCTION

As wildfires near urban areas have become more common, the health effects associated with exposure to wildfire smoke have also become more prevalent. It is widely understood that exposure to the pollutants released in wildfire smoke, such as particulate matter and carbon monoxide, can be damaging to human health (CDC; U.S. EPA). While statistics on the number of individuals who seek medical care as a result of exposure to these pollutants are sometimes released, in general, little is known about the full range of health effects the majority of residents exposed to wildfire smoke experience (Kunzli et al., 2006; Vedal, 2006; Morgan, 2010). Likewise, little is known about the costs imposed on individuals as a result of exposure to wildfire smoke and the associated health effects (Dale, 2009; Kochi et al., 2010). Recent studies such as Pinto-Prades et al. (2009) point out the need for attaching monetary values to health effects if proper decision-making based on cost-benefit analyses are to be made.

The epidemiological studies which have conducted surveys after wildfire events to measure acute health effects have found a positive correlation between wildfire smoke and a range of health damages (Mott et al., 2002; Kunzli et al., 2006). Further, these studies found that many individuals exposed to wildfire smoke change their behavior in an effort to defend themselves against the potential health damages that could result from exposure. When wildfires occur near residences, local air quality reports and public service announcements will often advise individuals exposed to the smoke to take particular actions to minimize their exposure, such as staying indoors and running the air conditioner. During the 2003 Southern California wildfires, Kunzli et al. (2006) found that children with asthma were more likely to take preventative actions such as wearing masks and staying indoors to minimize their exposure to the smoke. Mott et al. (2002) found that during a 1999 wildfire in northern California near the Hoopa Valley National Indian Reservation, residents took actions such as wearing face masks, evacuating, running high-efficiency particulate air cleaners in the home and following public service announcements which advised them to take these actions.

While these epidemiological studies confirm that individuals experience minor health effects from exposure to wildfire smoke and many individuals change their behavior to defend themselves from these damages, there is a lack of economic research on the cost imposed on individuals as a result of this exposure. The majority of the literature which has attempted to capture the economic cost of health damages from wildfire smoke has relied on secondary data and benefit transfer methods based on low levels of long-term exposure to urban air pollution. The few studies which have used primary data to calculate these costs have ignored behavioral responses to wildfire smoke exposure as well as the disutility associated with health effects or lost leisure. Neidell (2004) notes that while numerous studies attempt to capture the effects of pollution on health, many neglect to properly account for these behavioral responses. This information is important not only from a human welfare standpoint, but also plays a role in public policy debates about the appropriate level of fire management practices given the effects of wildfires on exposed individuals.

Economic theory and non-market valuation techniques highlight the importance of incorporating into the individual utility maximization process the behavioral responses to and disutility of exposure to an environmental contaminant. Information on the investments of time and money made on defensive actions can be used to infer the true economic cost of pollution from wildfire smoke, or equivalently, the value an individual places on reductions in pollution, i.e., the individual willingness to pay (WTP). Neidell (2004) rightfully argues that the cost of these defensive actions individuals take when exposed to a pollutant cannot be ignored in a welfare analysis. Economic theory tells us that ignoring these behavioral responses and the value of disutility will result in an underestimate of the true value of a reduction in pollution. However, to our knowledge, this information has never been collected and analyzed after a major wildfire.

Using primary data from over 400 residents exposed to unhealthy levels of air quality during California's Station Fire of 2009, this study looks at 1) the full range of health effects experienced as a result of exposure to the wildfire smoke; 2) the defensive actions taken in response to this exposure, as well as the major determinants that motivates these actions and the expenditures made on these actions; 3) the individual willingness to pay for a reduction in pollution levels from wildfire smoke; and 4) the relationship between expenditures on defensive actions and willingness to pay.

II. THEORETICAL FRAMEWORK

The fact that individuals can choose to invest in defensive inputs which affect their production of some health output when exposed to an environmental contaminant is an underlying assumption of the defensive behavior method, commonly referred to as the averting behavior method. This is a revealed preference approach to non-market valuation which combines information about behavioral responses to pollution exposure with household production theory to infer the value of reducing the risk associated with exposure to a pollutant. When faced with exposure, it is assumed that individuals will choose to invest in defensive actions that reduce the health damages they could experience as long as the benefits of doing so exceed the costs (Dickie, 2003). While the defensive behavior method has been applied to a wide range of environmental contaminants, including but not limited to various air pollutants (Cropper, 1981; Gerking and Stanley, 1986; Joyce et al., 1989; Dickie, 2005), contaminated water supplies (Harrington et al., 1989; Um et al., 2002; Dasgupta, 2004); and nuisance pests (Jakus, 1994), to our knowledge it has never been applied to wildfire smoke specifically.

The basic framework underlying the defensive behavior method stems from a health production function first put forth by Grossman (1972) with extensions made by Cropper (1981) and Harrington and Portney (1987). Grossman's original model outlined an individual's demand for good health as a function of an inherited stock of health which depreciates over time and choice variables representing investments individuals make in their health. Here we present a simple one period model where an individual chooses his optimal level of health as a function of exogenous factors such as pollution, health status, lifestyle and demographic factors, as well as choice variables. These choice variables include investments of time and money in taking defensive actions to reduce his exposure to wildfire smoke or minimize the health effects experienced as a result of exposure. Defensive actions are broken down into what are referred to as averting and mitigating actions. Averting actions are those taken to decrease exposure to the pollutant that causes the negative health outcome, such as staying indoors or using an air cleaner in the home to reduce pollution concentrations. Mitigating actions represent those 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 method and the theoretical framework underlying it are explained in great detail in Dickie (2003) and Freeman (2003), so here we just summarize. An individual is assumed to maximize his level of utility, which is given by:

$$U = U\,(X, L, S) \qquad (3.1)$$

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

$$S = S\,(P, A, M, Z) \qquad (3.2)$$

where P represents exposure to a pollutant, A represents averting actions that can be taken to reduce exposure to the pollutant and thus the negative health outcome, M represents mitigating actions that can be taken to reduce the negative health outcome and Z represents a set of exogenous factors that can affect the health outcome, such as demographics and health status prior to exposure. It can be assumed that S is increasing in exposure to the pollutant and decreasing in averting and mitigating actions. Individuals are also subject to a budget constraint:

$$I + w\,[T - L - S\,(P, A, M, Z)] = X + p_A A + p_M M \tag{3.3}$$

where I represents non-labor income, w represents labor income, and the individual is assumed to allocate his total time available for work T between work, leisure and S. Averting activities have a price of $p_{A,}$ mitigating activities a price of p_M, and the price of X is normalized to 1. This can be solved as a utility maximization problem as well as an expenditure minimization problem. Focusing on the latter, the individual faces the following cost minimization problem:

$$\min X + p_A A + p_M M$$

$$\text{s.t. } S^* = S\,(P, A, M, Z) \tag{3.4}$$

which can be re-written as the Lagrangian:

$$L = X + p_A A + p_M M + \lambda(S^* - S\,(P, A, M, Z)) \tag{3.5}$$

Through first order conditions, we can solve for the values of A, M and λ that will produce a given level of sick time S^* at a minimum cost. These values will be a function of $p_{A,}$ $p_{M,}$ S, P, and Z. Following Bartik (1988) and Dickie (2003), these functions can be used to define the defensive expenditure function as follows:

$$\mathrm{D}\,(p_{A,}\, p_{M,,}\, S^*, P, Z) = p_A A^* + p_M M^* \tag{3.6}$$

This function represents the minimum expenditure that must be made on defensive actions to achieve a given amount of sick time at a specific pollution level and set of prices for averting and mitigating actions. Using the envelope theorem, the benefits of, or willingness to pay for, a small reduction in pollution equals:

$$\partial\, D(\cdot) \,/\, \partial P \tag{3.7}$$

This is the savings in defensive expenditures needed to achieve the original level of S given a change in pollution levels. It should be noted that equation (3.7) assumes that S stays constant. However, this may not equal the actual, or observed, change in defensive expenditures due to the fact that as individuals adjust their defensive expenditures in response to a change in pollution, sick days will also likely change. If that is the case, the observed change in defensive expenditures provides a lower bound on compensating variation (see Courant and Porter, 1981; Harrington and Portney, 1987; Bartik, 1988). As derived in Harrington and Portney (1987), Alberini and Krupnick (2000), Freeman (2003) and others, the willingness to pay for a small decrease in pollution can be broken down into four components:

(a) Incurred medical expenses due to health effects from exposure to pollution

(b) Lost wages due to health effects from exposure to pollution

(c) Expenditures on averting actions taken to avoid health effects

(d) The disutility associated with symptoms or lost leisure

Therefore, the willingness to pay for a reduction in pollution levels includes the individual value of savings on all four of these components. Component (a) represents mitigating actions taken to alleviate health effects from pollution and components (a) and (b) together are referred to as the cost of illness (COI) resulting from exposure to a pollutant. Component (c) is referred to as averting expenditures. As concluded in Harrington and Portney (1987), the sum of the cost of illness components and the expenditures on averting actions will typically underestimate “true benefits” of pollution reduction in that they will include everything except for the value of disutility associated with symptoms or lost leisure, component (d). In this study, we explore this relationship for the specific application of wildfire smoke exposure. First, the cost of illness and averting expenditures associated with exposure to the smoke will be quantified. Second, the willingness to pay for a reduction in pollution levels from the smoke will be measured by applying equation (3.7). While theory tells us willingness to pay will be larger, we attempt to quantify the magnitude of this difference to capture the value of disutility associated with exposure to wildfire smoke. Since the observed change in defensive expenditures given a change in pollution levels may provide a lower bound on compensating variation, this will provide insights into the proportion and magnitude of the minimum value of the monetary loss associated with the disutility of symptoms and lost leisure.

III. EMPIRICAL APPLICATION: WILDFIRE SMOKE FROM THE STATION FIRE

California's Station Fire of 2009 was the focus for this study. Residents in surrounding communities were exposed to unhealthy concentrations of pollution during this wildfire and many individuals took defensive actions to minimize their exposure to the wildfire smoke or the health effects that could result. See Chapter 2 for a complete description of the study area, survey design, data collection, and sample statistics.

IV. ESTIMATING THE COST OF ILLNESS AND AVERTING EXPENDITURES

Econometric Models

Given that the mitigating and averting actions individuals undertake when exposed to a pollutant are an important component of the defensive behavior method, probit regression models are estimated to identify the determinants of each mitigating and averting action taken by respondents during the Station Fire and then used to calculate the predicted probability that each action is taken. As explained in Section 2, these decisions will be a function of prices, the negative health outcome, pollution levels, as well as any other exogenous factors that could influence the decision to undertake these actions. The reported costs of actions taken could not be included in the regression models given that anytime the price is greater than zero this variable predicts the outcome of undertaking the associated action perfectly. The number of symptoms and the level of pain experienced are included as the measure of the negative health outcome, and both objective and subjective pollution levels are included. Given high correlation between the number of days smoke was smelled both inside and outside the home and findings by Kunzli et al. (2006) that the number of days smoke was smelled indoors was a very important determinant of health effects experienced and mitigating actions taken during the 2003 Southern California wildfires, we focus on this measure for subjective pollution levels. Given the relatively small number of individuals who smelled smoke indoors for more than ten days, respondents were categorized into those smelling smoke indoors for 1-5 days and those smelling smoke indoors for greater than five days. For objective pollution levels, since measures of PM10 concentrations were available for the city of Glendora only and PM2.5 concentrations were available for the cities of Glendora and Burbank only, we chose to include six day averages of daily maximum carbon monoxide concentrations as the measure of objective pollution levels during the Station Fire.

These probit regression models will control for factors that influence an individual’s decision to undertake each mitigating or averting action. By setting independent variables at their mean, the predicted probability that each action is taken can then be calculated. An estimate of the average household's predicted cost of illness and averting expenditures due to wildfire smoke can then be quantified using a simple formula similar to one presented in Alberini and Krupnick (2000) as follows:

$$\sum_d [p_d * \Phi(\bar{x} * \beta_d)] \qquad (3.8)$$

where d represents each possible averting or mitigating action, p_d represents the average in-sample reported cost of taking each action, and Φ represents the predicted probability that the action is taken, based on all households, with independent variables set at their mean (based on the standard normal cdf). Recall that for averting actions, respondents were asked to report the range of days that each action was taken. As a result, the in-sample reported cost of taking each averting action will be averaged based on the range of days the action was taken. Summing across all mitigating actions gives an estimate of the predicted cost of illness and summing across all averting actions gives an estimate of the predicted averting expenditures for the average household during the Station Fire.

Results: Regression Models

Table 3.1 presents the results of regression analyses identifying the factors that influence the decision to take four mitigating actions as a direct result of symptoms experienced from exposure to smoke from the Station Fire: visiting a doctor or taking prescribed medications, taking nonprescription medications, missing work, and losing days of recreation activities.[11] In each regression, the dependent variable is coded with a 1 if the mitigating action was taken and 0 otherwise.

[11] Given the very small number of respondents who went to a non-traditional healthcare provider as a result of symptoms (5 individuals), a model was not estimated for this mitigating activity.

TABLE 3.1
Determinants of Mitigating Actions (Probit)

	Doctor/Prescription Meds.		Non-prescription Meds.		Missed Work		Missed Recreation	
Variable	*Coeff.*	*Std. Error*	*Coeff.*	*Std. Error*	*Coeff.*	*Std. Error*	*Coeff.*	*Std. Error*
Days smoke smelled indoors								
1-5 DAYS	-0.065	0.521	0.342	0.298	1.416	1.020	0.319	0.273
> 5 DAYS	-0.957	0.654	0.250	0.346	1.607	1.114	0.292	0.305
Average daily maximum CO concentration	-1.290	2.220	-0.797	1.331	1.786	2.373	1.126	1.110
Number of symptoms	**0.773****	0.308	**0.341***	0.185	0.765	0.505	**0.594*****	0.196
Level of pain from symptoms	**0.670*****	0.227	**0.348*****	0.129	0.096	0.389	**0.580*****	0.145
Current respiratory condition	**0.806***	0.420	**-0.717****	0.341	-1.019	0.849	-0.230	0.343
Current heart condition	-0.419	0.679	-0.753	0.522	0.227	1.115	**-1.017****	0.442
Experienced health effects from wildfire smoke in past	**-1.266****	0.551	0.423	0.272	0.021	0.862	0.423	0.270
Times per week of exercise	-0.261	0.273	-0.152	0.155	0.455	0.429	**0.297****	0.149
Smoker	0.875	0.608	-0.984	0.737	0.244	1.225	0.563	0.409
Alcoholic drinks per week	-0.047	0.331	0.137	0.172	-0.296	0.578	0.189	0.160
Current health is excellent	-1.343	1.168	-1.212	1.051	2.708	375.690	-0.610	1.345
Current health is good	-0.777	1.120	-1.206	1.018	2.433	375.689	-0.768	1.308
Current health is fair	-1.192	1.059	-1.209	0.998	(omitted)		-0.115	1.272
Hours per week of indoor recreation	-0.052	0.074	-0.009	0.035	**-0.449****	0.212	-0.024	0.039
Hours per week of outdoor recreation	-0.051	0.045	0.010	0.025	0.042	0.057	-0.025	0.026
Has a regular doctor	(omitted)		-0.114	0.402	-0.893	0.792	0.217	0.390
Male	**-1.404*****	0.526	**-0.535***	0.274	**-1.973*****	0.756	**-0.517****	0.261
Married	0.699	0.502	-0.130	0.294	0.900	0.942	**0.703****	0.308
Age	-0.011	0.017	0.001	0.011	0.003	0.031	**-0.025****	0.010
White	0.119	0.497	-0.027	0.318	-1.307	0.830	-0.167	0.316
Graduate school graduate	-0.012	0.522	-0.237	0.312	0.668	0.643	**0.786****	0.319
College graduate	0.569	0.461	0.317	0.280	0.537	0.831	-0.053	0.279
Employed full-time	-0.428	0.579	0.221	0.351	1.465	0.913	-0.041	0.328
Employed part-time	0.196	0.862	-0.989	0.686	0.427	1.165	0.321	0.472
Has health insurance	1.198	0.772	0.675	0.503	-0.093	1.007	-0.433	0.513
Lives in Duarte	0.050	0.659	-0.423	0.447	(omitted)		**-0.713***	0.408
Lives in Monrovia	-0.414	0.566	-0.050	0.322	-0.364	0.794	0.383	0.331
Lives in Burbank	-0.164	0.522	0.100	0.327	(omitted)		-0.140	0.309
Income	-0.004	0.005	0.002	0.003	0.004	0.007	-0.001	0.003
Heard or read about possible health effects	0.047	0.624	-0.377	0.337	1.134	0.877	-0.377	0.324
Believes smoke can affect health	(omitted)		(omitted)		(omitted)		0.261	0.527
Constant	-0.207	3.377	0.048	2.357	-10.046	375.730	-2.076	2.324
N =	339		338		193		372	
Log Likelihood	-39.694		-88.036		-23.254		-94.263	
LR chi2	99.080		103.710		53.910		263.210	
Prob > chi2	0.000001		0.000001		0.002300		0.000001	

*: p < 0.10, **: p < 0.05, ***: p < 0.01

A few observations from Table 3.1 should be noted. These models show that the greater the number of symptoms or the higher the level of pain experienced from symptoms, the more likely it is that the individual went to the doctor or took prescribed medications, took nonprescription medications, and lost recreation, all else constant. This is not surprising given that mitigating actions are taken as direct result of symptoms experienced, so it would be assumed that as the number of symptoms or their severity increases, so does the probability that mitigating actions are taken. In terms of variables that capture an individual's health history, those respondents who have a chronic respiratory disease that was present in the last year are more likely to visit the doctor or take prescribed medications for smoke-related symptoms but less likely to take non-prescription medications. Individuals who have a current heart condition that was present in the last year are less likely to miss recreation as a result of symptoms. In addition, individuals who have previous experience with health effects from wildfire smoke are less likely to visit the doctor or take prescribed medications for symptoms.

Turning to lifestyle factors, the more an individual exercises per week, the more likely they are to lose days of recreation as a result of symptoms. An increase in the hours per week spent in indoor recreation activities has a negative and statistically significant effect on the likelihood of missing work days due to symptoms. Various demographic factors such as sex, marital status, age, education level, and location are also found to have a significant effect on the decision to undertake certain mitigating actions. Similar to Kunzli et al. (2006) we find no clear association between objective, community-wide pollution concentrations and mitigating activities due to symptoms from wildfire smoke exposure. This could be due to the lack of variation in this variable, as well as Kunzli et al.'s (2006) explanation that objective measures do not account for spatial differences in smoke dispersion within the community.

Table 3.2 presents the results of regression analyses identifying the factors that influence the decision to undertake eight averting actions to reduce exposure to smoke from the Station Fire: evacuating the area, wearing a face mask, running the air conditioner more in the home, using an air cleaner in the home, removing ashes from property, avoiding going to work, staying indoors, and avoiding normal outdoor recreation activities. In each regression, the dependent variable is coded with a 1 if the averting action was taken and 0 otherwise.

TABLE 3.2
Determinants of Averting Actions (Probit)

	Evacuated		Wore a face mask		Ran air conditioner		Used home air cleaner	
Variable	*Coeff.*	*Std. Error*	*Coeff.*	*Std. Error*	*Coeff.*	*Std. Error*	*Coeff.*	*Std. Error*
Days smoke smelled indoors								
1-5 DAYS	**0.847****	0.423	0.398	0.295	**0.572*****	0.176	-0.003	0.208
> 5 DAYS	0.389	0.492	0.115	0.364	**0.508****	0.214	0.307	0.230
Average daily maximum CO concentration	**3.354****	1.472	0.483	1.316	0.138	0.802	-0.088	0.917
Number of symptoms	-0.300	0.263	**0.558*****	0.194	-0.073	0.165	**0.4533*****	0.158
Level of pain from symptoms	**0.659*****	0.201	-0.096	0.155	**0.232***	0.119	0.000	0.113
Current respiratory condition	0.366	0.444	-0.252	0.373	0.219	0.269	-0.067	0.258
Current heart condition	**1.086****	0.539	-0.313	0.515	0.135	0.293	-0.105	0.322
Experienced health effects from wildfire smoke in past	-0.109	0.411	-0.060	0.319	**0.402***	0.224	0.113	0.224
Hours per week of indoor recreation	0.058	0.048	-0.005	0.032	0.014	0.020	-0.035	0.026
Hours per week of outdoor recreation	-0.001	0.032	0.014	0.019	-0.014	0.014	-0.003	0.017
Has a regular doctor	-0.532	0.462	0.260	0.428	0.084	0.233	0.329	0.282
Male	-0.377	0.373	-0.090	0.274	-0.057	0.178	-0.132	0.195
Married	**0.835***	0.450	-0.070	0.287	**0.397****	0.188	**0.407***	0.223
Age	**-0.039****	0.017	-0.009	0.013	0.002	0.008	-0.010	0.009
White	0.654	0.446	-0.189	0.318	-0.034	0.198	0.078	0.231
Graduate school graduate	0.381	0.378	-0.251	0.354	0.217	0.210	0.174	0.232
College graduate	0.598	0.443	0.114	0.266	**-0.343****	0.174	0.145	0.197
Employed full-time	0.457	0.501	0.119	0.341	-0.034	0.220	**0.556****	0.253
Employed part-time	-0.714	0.946	-0.388	0.558	-0.150	0.326	0.397	0.373
Has health insurance	-0.718	0.529	-0.291	0.404	-0.055	0.319	0.490	0.348
Months at current zip code	0.001	0.001	0.001	0.001	0.000	0.000	0.000	0.001
Number of children under 18 years old in household	0.273	0.184	0.125	0.151	**0.172***	0.101	-0.063	0.107
Lives in Duarte	0.801	0.573	-0.052	0.407	-0.338	0.258	-0.419	0.305
Lives in Monrovia	0.572	0.456	0.224	0.318	-0.159	0.216	-0.404	0.262
Lives in Burbank	-0.503	0.469	-0.339	0.382	-0.118	0.212	0.042	0.232
Income	-0.003	0.004	-0.003	0.003	0.002	0.002	**-0.006*****	0.002
Heard or read about possible health effects	0.030	0.503	0.352	0.404	0.162	0.217	0.299	0.266
Believes smoke can affect health	(omitted)		-0.310	0.429	**0.523****	0.257	**0.943***	0.504
Constant	**-7.013*****	2.717	-2.270	2.193	-1.250	1.381	-2.441	1.600
N =	335		369		369		369	
Log Likelihood	-47.964		-76.304		-202.946		-156.796	
LR chi2	61.050		40.570		76.510		79.820	
Prob > chi2	0.000		0.059		0.000001		0.000001	

*: p < 0.10, **: p < 0.05, ***: p < 0.01

TABLE 3.2
Determinants of Averting Actions (Probit), cont.

	Removed ashes		Avoided going to work		Stayed indoors		Avoided recreation	
Variable	*Coeff.*	*Std. Error*	*Coeff.*	*Std. Error*	*Coeff.*	*Std. Error*	*Coeff.*	*Std. Error*
Days smoke smelled indoors								
1-5 DAYS	**0.442*** **	0.169	0.618	0.408	**0.447** **	0.199	**0.437** **	0.214
> 5 DAYS	**0.634*** **	0.203	**1.033** **	0.457	**0.680** **	0.269	**0.631** **	0.292
Average daily maximum CO concentration	-1.294	0.805	-0.933	1.753	0.770	0.992	1.642	1.255
Number of symptoms	0.200	0.153	-0.144	0.260	**0.536***	0.312	-0.021	0.264
Level of pain from symptoms	-0.028	0.108	0.132	0.202	0.097	0.174	**0.379** **	0.189
Current respiratory condition	-0.245	0.251	-0.220	0.437	0.189	0.356	0.148	0.392
Current heart condition	**0.518***	0.289	0.736	0.506	0.156	0.336	**0.909** **	0.418
Experienced health effects from wildfire smoke in past	0.036	0.207	0.525	0.408	0.046	0.282	0.147	0.305
Hours per week of indoor recreation	-0.030	0.020	0.022	0.034	0.023	0.023	0.003	0.025
Hours per week of outdoor recreation	**0.026** **	0.013	0.035	0.025	0.011	0.015	**0.034** **	0.017
Has a regular doctor	0.112	0.231	-0.516	0.433	-0.030	0.275	-0.473	0.318
Male	-0.161	0.173	0.044	0.350	**-0.378***	0.215	-0.369	0.233
Married	-0.134	0.181	0.119	0.397	**0.812*** **	0.218	**0.553** **	0.234
Age	**-0.019*** **	0.007	0.009	0.014	**-0.018***	0.009	**-0.027*** **	0.010
White	0.197	0.191	-0.051	0.429	-0.322	0.243	0.047	0.244
Graduate school graduate	0.116	0.201	-0.164	0.398	0.318	0.244	0.012	0.254
College graduate	-0.061	0.166	**0.650***	0.384	-0.184	0.201	-0.103	0.219
Employed full-time	-0.072	0.215	0.099	0.413	-0.321	0.260	-0.005	0.277
Employed part-time	-0.456	0.306	(omitted)		-0.413	0.383	-0.390	0.397
Has health insurance	0.010	0.300	-0.004	0.530	0.261	0.397	0.522	0.409
Months at current zip code	0.001	0.000	**-0.003** **	0.001	0.000	0.001	0.000	0.001
Number of children under 18 years old in household	-0.032	0.092	-0.330	0.231	0.207	0.128	0.175	0.136
Lives in Duarte	0.050	0.252	(omitted)		-0.082	0.301	-0.203	0.307
Lives in Monrovia	-0.153	0.209	-0.063	0.403	-0.027	0.252	0.053	0.270
Lives in Burbank	0.028	0.206	-0.020	0.447	0.086	0.259	-0.156	0.292
Income	-0.002	0.002	-0.002	0.004	0.001	0.002	**-0.004***	0.002
Heard or read about possible health effects	**0.709*** **	0.218	0.518	0.630	0.317	0.249	0.245	0.258
Believes smoke can affect health	0.081	0.251	(omitted)		0.228	0.265	**0.723*** **	0.269
Constant	2.178	1.373	-1.452	2.951	-0.672	1.713	-1.330	2.054
N =	369		274		369		369	
Log Likelihood	-217.776		-51.443		-147.685		-128.511	
chi2	63.010		29.920		107.690		104.380	
Prob > chi2	0.0002		0.227		0.000001		0.000001	

*: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

These models show some similarities with respect to the variables found to influence the demand for averting actions. Perceived pollution levels as measured by the number of days smoke is smelled indoors has a positive and significant effect on the predicted probability that households engaged in all averting activities except wearing a face mask and using a home air cleaner, compared to not smelling smoke inside the home at all. This is similar to previous findings that perceived pollution levels can have a positive impact on the decision to take averting actions. Abdalla et al. (1992) and Abrahams et al. (2000) found that perception of risk from tap water was an important determinant of averting actions taken in response to contamination. In a survey of U.S. citizens facing arsenic contamination in their drinking water, Jakus et al. (2009) found that perceived water quality played a large role in the decision to buy bottled water.

Objective pollution concentrations of carbon monoxide have a positive and significant effect on the predicted probability of evacuating during the Station Fire. This is similar to previous findings that the probability of mitigation increases with actual pollution concentrations (Akerman et al., 1991; Doyle et al., 1991; Smith et al., 1995). The greater the number of symptoms experienced, the more likely it is that the individual will wear a face mask, use an air cleaner in the home, and stay indoors. In addition, the higher the level of pain experienced, the more likely the individual is to evacuate, run the air conditioner more, and avoid recreation activities. Similarly, Berger et al. (1987) found that individuals who experienced various health symptoms in the year prior to being surveyed were more likely to buy air conditioners and air purifiers for health reasons.

Previous literature finds that individuals with preexisting conditions as well as those who have had prior experience with health damages from the pollutant at hand are more likely to engage in defensive activities to protect themselves from health damages. For instance, Kunzli et al. (2006) found that during the 2003 Southern California wildfires, children with asthma were more likely to take preventative actions such as wearing masks and staying indoors to avoid the exposure to the smoke. Similarly, we find that individuals who had a heart disease within the last 12 months are more likely to engage in averting activities such as evacuating the area impacted by smoke during the fire, removing ashes from their property, as well as avoiding normal outdoor recreation activities. In addition, individuals who have experienced health effects as a result of exposure to wildfire smoke in the past are more likely to run their air conditioner more to avoid health damages from smoke from the Station Fire. Similarly, Bresnahan et al. (1997) found that households who had previously experienced symptoms in smoggy conditions were more likely to engage in defensive activities when pollution levels were high.

Variables that capture lifestyle factors were also found to influence the decision to engage in certain averting activities. For instance, the number of hours an individual spends in a typical week engaging in outdoor recreation activities is found to have a positive and statistically significant effect on removing ashes from property and avoiding normal outdoor recreation activities in an effort to minimize exposure to the smoke from the Station Fire. Finally, various demographic factors such as sex, marital status, age, education level, income, employment status, and presence of children in the household are found to have a significant effect on the decision to undertake certain averting actions.

Individuals who heard or read about the health effects of wildfire smoke from public service announcements, news articles or local air quality reports are more likely to remove ashes from their property and individuals who believe that exposure to wildfire smoke can affect a person's health are more likely to run their air conditioner more, use an air cleaner in their home and avoid normal outdoor recreation activities as a result of the smoke from the Station Fire. These results are not surprising given that information received, as well as attitudes and beliefs about the health effects of a particular pollutant have been repeatedly found to significantly impact the decision to take defensive actions (Smith and Desvousges, 1986; Abdalla et al., 1992; Abrahams et al., 2000). Variables such as having a current chronic respiratory disease, race, having health insurance, and location do not have a statistically significant effect on the decision to undertake any averting action.

Results: Cost of Illness and Averting Expenditures

The predicted cost of illness and averting expenditures are calculated by applying equation (3.8). The predicted probability that each mitigating and averting action is taken is calculated from the regression models in Tables 3.1 and 3.2. Each model is re-estimated including only those independent variables which were found to have a significant effect on the decision to undertake each activity in order to reduce the variance in the predicted cost estimate. Given the small number of respondents who reported taking certain averting actions for more than ten days, the predicted probability of taking each averting action is multiplied by the average in-sample cost of taking each action for 1-5 days and greater than 5 days. Table 3.3 presents results for the predicted cost of illness and Table 3.4 presents results for predicted averting expenditures.

TABLE 3.3
Predicted Cost of Illness

Mitigating Action	*Predicted Probability Action is Taken*	*Average Expenditure*	*Predicted Expenditure*
Obtained medical care/prescription medications	0.0084	$77.87	$0.65
Took non-prescription medicines	0.0602	$16.86	$1.01
Missed work	0.0140	$691.76	$9.68
Lost days of recreation activities	0.1515	N/A	N/A
Average Cost of Illness			$11.34

TABLE 3.4
Predicted Averting Expenditures

Averting Action	Predicted Probability Action is Taken	Average Expenditure 1-5 days	Average Expenditure > 5 days	Predicted Expenditure 1-5 days	Predicted Expenditure > 5 days
Evacuated	0.0136	$204.41	$440.00	$2.78	$5.98
Wore a mask	0.0515	$3.95	$12.00	$0.20	$0.62
Ran air conditioner more than usual	0.6219	$12.78	$34.08	$7.95	$21.19
Used an air cleaner, filter or humidifier	0.1843	$15.17	$33.48	$2.80	$6.17
Removed ashes from property	0.5871	$6.10	$13.48	$3.58	$7.91
Avoided going to work	0.0407	$177.50	$320.00	$7.22	$13.02
Stayed indoors more than usual	0.8125	N/A	N/A	N/A	N/A
Avoided normal outdoor recreation/exercise	0.8638	N/A	N/A	N/A	N/A
Average Averting Expenditures				$24.53	$54.89

A cost of illness estimate for an average household during the Station Fire is $11.34. This cost measure is conservative in that there is no assumed cost to the individual of lost days of recreation activities due to symptoms. Averting activities cost an average household $24.53 if they are taken for 1-5 days and $54.89 if they are taken for more than 5 days.[12] This expenditure measure is also conservative in that there is no assumed cost to the individual of staying indoors or avoiding normal outdoor recreation activities/exercise to reduce exposure to the smoke. The sum of the cost of illness and averting expenditures account for all aspects of the individual value of a reduction in pollution from the Station Fire smoke except for the value of disutility associated with symptoms and lost leisure.

[12] Taking a simple in-sample average results in a cost of illness estimate of $13.79 for the average household and a cost of averting activities estimate of $32.96 for the average household. Calculating these in-sample averages may be more appealing to policy-makers than the approach taken here due to the fact that they do not require any regression analysis.

V. ESTIMATING THE WILLINGNESS TO PAY FOR A REDUCTION IN PERCEIVED POLLUTION LEVELS

Econometric Model

Those individuals who took some defensive action in response to the Station Fire smoke had to make a decision about the intensity of these actions. Defensive expenditures are the sum of all expenditures the individual makes on both averting and mitigating actions, and they are often used to proxy this decision about the intensity of defensive actions (Abdalla et al., 1992; Um et al., 2002). As shown in equation (3.6), these expenditures will be a function of anything that averting and mitigating actions are a function of, including prices, the negative health outcome, pollution levels, as well as any exogenous factors that could affect the level of expenditures made. Regression analysis is used to model the determinants of these expenditures. Again, the number of symptoms and the level of pain experienced are included as the measure of the negative health outcome, and both objective and subjective pollution levels are included in the model. Given that the data on defensive expenditures is censored at $0, a tobit regression model is estimated to determine the factors that significantly influence defensive expenditures. As shown in equation (3.7) the marginal effect of pollution levels on defensive expenditures gives an estimate of the individual willingness to pay for a decrease in pollution levels, assuming the negative health outcome stays constant. If individuals adjust their health outcome, the observed change in defensive expenditures will provide a lower bound on compensating variation.

Results: Regression Model

The results of the regression analysis are presented in Table 3.5.

TABLE 3.5
Determinants of Defensive Expenditures (Tobit)

	Full		Reduced	
Variable	*Coefficient*	*Std. Error*	*Coefficient*	*Std. Error*
Days smoke smelled indoors				
1-5 DAYS	**53.460***	32.308	**60.652****	29.743
> 5 DAYS	**99.646*****	37.175	**106.002*****	33.843
Average daily maximum CO concentration	67.138	140.074		
Number of symptoms	12.671	25.491		
Level of pain from symptoms	**54.745*****	18.465	**60.704*****	9.314
Current respiratory condition	**-73.118***	42.834	-64.094	38.940
Current heart condition	62.820	50.413		
Experienced health effects from wildfire smoke in past	2.117	36.025		
Heard or read about possible health effects	**68.951***	41.770	46.435	38.195
Believes smoke can affect health	18.300	55.951		
Hours per week of indoor recreation	0.574	3.770		
Hours per week of outdoor recreation	0.497	2.393		
Has a regular doctor	5.889	42.051		
Male	-26.656	31.614		
Married	33.491	34.822		
Age	-1.566	1.400		
White	**-63.265***	36.670	-50.058	32.024
Graduate school graduate	30.255	37.507		
College graduate	16.916	31.241		
Income	0.243	0.330		
Employed full-time	-6.893	39.336		
Employed part-time	-67.428	59.224		
Number of children under 18 years old in household	3.147	16.895		
Months at current zip code	0.034	0.093		
Has health insurance	79.953	54.400		
Lives in Duarte	**-122.763****	48.337	**-123.302*****	41.393
Lives in Monrovia	-18.379	38.765		
Lives in Burbank	-6.790	37.776		
Constant	-227.183	244.576	-70.552	49.300
sigma	**223.252*****	9.828	**224.834*****	9.650
N =	333		361	
Log Likelihood	-1832.037		-1938.756	
LR chi2	86.250		76.410	
Prob > chi2	0.0000001		0.000001	

*: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

Only those variables which were found to have a statistically significant effect on defensive expenditures are retained in the reduced version of the model in the right-hand column. Individuals who smelled smoke inside their home for one to five days or greater than five days have higher defensive expenditures than those who did not smell smoke inside their home during the Station Fire, all else constant. Similarly, a questionnaire administered to Korean households by Um et al. (2002) showed that individuals perceived water quality was a significant determinant of the intensity of expenditures made on averting actions to avoid polluted tap water. In addition, from a survey of U.S. residents, Jakus et al. (2009) found that those individuals who perceived their risk from drinking tap water to be high had greater expenditures on bottled water than those with lower perceived risk. Table 3.5 also shows that objective, community-wide measures of carbon monoxide do not have a significant effect on defensive expenditures.

The level of pain from symptoms experienced has a positive and statistically significant effect on defensive expenditures, all else constant. Having a respiratory condition that was present in the last year has a negative and statistically significant effect on defensive expenditures at the 10% level in the full model however, in the reduced version of the model which includes more data points this variable is no longer statistically significant. Individuals who heard or read about the health effects of wildfire smoke from public service announcements, news articles or local air quality reports spent more on defensive expenditures than those who did not in the full model. In addition, being white has a negative and statistically significant effect on defensive expenditures in the full model. However, while both of these variables are statistically significant at the 10% level in the full model they are no longer significant at standard significance levels in the reduced model. Finally, living in the city of Duarte has a negative and significant effect on the level of defensive expenditures.

Results: Willingness to Pay

Given that only perceived pollution levels as measured by the number of days wildfire smoke was smelled inside the home is found to be a significant determinant of defensive expenditures, we estimate the willingness to pay for a decrease in perceived pollution levels similar to the approach taken by Um et al. (2002). From Table 3.5, focusing on the best fit reduced model, defensive expenditures are shown to be $60.65 higher when smoke is smelled indoors for 1-5 days compared to zero days, so this represents the individual value of, i.e. the willingness to pay for, a reduction in smoky days from 1-5 to zero. The individual willingness to pay for a reduction in smoky days from greater than five days to zero is $106.00. This represents a lump-sum willingness to pay given that the wildfire is a one-time event. Recall that if individuals adjust their negative health outcome in response to a change in pollution levels, this observed value represents a lower bound on compensating variation.

There are no previous studies which have attempted to capture this value for the pollutants associated with wildfire smoke specifically, but a few have applied the defensive behavior method to value decreases in other air pollutants. Using a health production function approach, Gerking and Stanley (1986) estimated marginal willingness to pay for the average employed person to be between $18-24 per year for a 30% reduction in ambient ozone in 1986 dollars. A few years later, Dickie and Gerking (1991) estimated willingness to pay for a uniform one part per ten million reduction in ozone, nitrogen dioxide and carbon monoxide to be \$1.20 and \$1.22 per person per day for impaired and normal subsamples, respectively.

VI. COMPARISON OF PREDICTED COST OF ILLNESS AND AVERTING EXPENDITURES WITH WILLINGNESS TO PAY

The sum of the cost of illness and averting expenditures include all components of the willingness to pay for a small decrease in pollution levels except for the disutility associated with symptoms or lost leisure. To explore this relationship in the data presented here, Figure 3.1 presents a comparison of total predicted cost of illness and averting expenditures from Tables 3.3 and 3.4 with willingness to pay estimates for a small decrease in perceived pollution levels from Table 3.5. Recall that averting expenditures are estimated for a given range of days they are taken (1-5 days and greater than five days) and similarly, willingness to pay is estimated for a given range of days that smoke is smelled indoors (1-5 days and greater than five days). The cost of illness is not broken down into a range of days, as respondents were simply asked to report their total expenditure on each mitigating action. The predicted cost of illness of \$11.34 is added to each range of averting expenditures. It appears that during the Station Fire, theory underlying the defensive behavior method is supported and the sum of cost of illness and averting expenditures provides a lower bound to the true economic value of a reduction in pollution levels. Theory tells us that willingness to pay should exceed the sum of these two components due to the disutility associated with symptoms and lost leisure. Taking the difference of these two measures results in an estimate of the value of disutility of \$24.78 for 1-5 days of exposure to wildfire smoke and \$39.77 for greater than five days. Our empirical analysis shows that the disutility of symptoms and lost leisure represents at least 38-41% of total willingness to pay for the case of wildfire smoke. In a study valuing changes in health risks, Berger et al. (1987) found that when asked to rank their reasons for valuing symptom relief, 66% of respondent's ranked comfort as the most important, suggesting that the value of disutility associated with symptoms is high for many people.

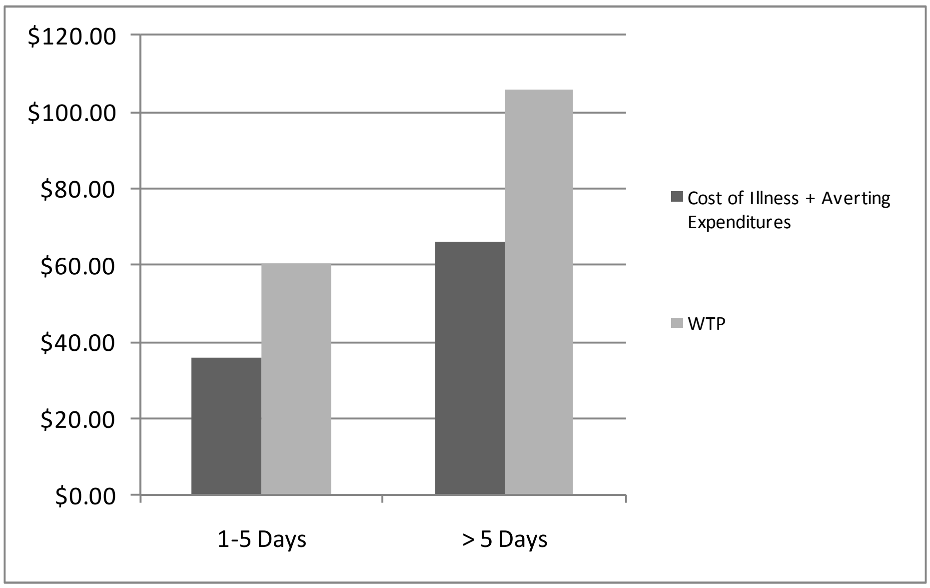

FIGURE 3.1
Cost of Illness and Averting Expenditures vs. WTP for a Reduction in Perceived Pollution Levels

VII. CONCLUSIONS

Wildfire smoke will continue to be a source of concern in the public health arena, however, little is known about the full range of health effects the majority of residents exposed to wildfire smoke experience and all of their associated costs. This study contributes to the scarce amount of published survey data which questions individuals directly about the health damages experienced and behavioral responses taken during a major wildfire event. Our study shows that 89% of individuals chose to take defensive actions to protect themselves from potential health damages resulting from exposure to wildfire smoke and to mitigate the health damages experienced. The majority took preventative, averting actions to minimize their exposure to the smoke, such as using a home air cleaner or running their air conditioner more, removing ashes from their property, and staying indoors or avoiding recreation activities during the wildfire event. A smaller proportion took mitigating actions to alleviate the health effects experienced during the Station Fire. For the first time, we explore the determinants of whether these averting and mitigating actions are taken during a wildfire and find that factors such as the number of days smoke was smelled indoors is a good predictor of whether certain actions are taken.

In addition, this unique natural experiment is used to explore the investments of time and money individuals are making on these defensive actions during a major wildfire event. We estimate predicted averting expenditures for the average household to be $24.53 and $54.89 depending on the number of days they are taken. Predicted cost of illness for the average household is estimated to be $11.34. Theory and past literature (Wu and Huang, 2001; Pattanayak et al., 2005) show that these expenditures provide a lower bound to the true economic value of decreased pollution levels.

Based on a tobit regression model of defensive expenditures, we find that individuals would be willing to pay $60.65 for 1-5 less days of smoke smelled indoors and $106.00 for greater than five less days. The discrepancy between the cost of illness and averting expenditure components and willingness to pay values supports the theoretical finding that the former lack the value of disutility associated with exposure to a pollutant, such as those contained in wildfire smoke. We estimate this value of disutility to be at least 38-41% of total willingness to pay depending on the number of days the individual is exposed to the wildfire smoke. Thus, the sum of the cost of illness and averting expenditures associated with exposure to wildfire smoke yields a substantial underestimate of willingness to pay.

As explained in Pattanayak et al. (2005), comparison of both defensive expenditures and willingness to pay values can shed light on calibration factors which can be used to adjust defensive expenditures into comprehensive economic values associated with decreased pollution levels. Given that this is the first study to estimate either for the specific case of exposure to wildfire smoke, we hope this is the first of many future studies to explore this relationship. The defensive behavior method is not without its problems and the willingness to pay estimates derived from it should be used cautiously (see Dickie, 2003; Freeman, 2003). However, the information collected to apply the defensive behavior method provides valuable insight into the behavioral responses to wildfire smoke exposure and the associated investments of time and money individuals are making on defensive actions. In addition, calculating the change in observed defensive expenditures given a change in pollution levels provides a relatively simple extension to arrive at a lower bound on compensating variation, a value much closer to the true benefits of a reduction in pollution levels than the sum of cost of illness and averting expenditures. Given expectations of more intense wildfire events near urban areas in the future, human exposure to wildfire smoke and interest in the resulting welfare implications will likely become more prevalent.

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CHAPTER FOUR

Valuing Morbidity from Wildfire Smoke Exposure: A Methodological Comparison of Revealed and Stated Preference Techniques

I. INTRODUCTION

A variety of environmental contaminants can negatively affect human health and a major mission of agencies such as the U.S. Environmental Protection Agency (EPA) is to protect human health by reducing human exposure to contaminants in the air, water and land (U.S.EPA, Human Health). Branches of the U.S. EPA such as the National Center for Environmental Economics are responsible for analyzing the economic impacts, i.e. costs and benefits, of environmental regulations and policies. However, the challenge of accurately monetizing the economic cost of the health damages associated with exposure to pollution has remained pervasive in the economics literature, as well as the policy realm.

In the past, economists relied on a simple cost of illness (COI) approach to estimate the economic cost of morbidity from pollution exposure. This is often calculated based on a damage function, which translates pollution concentrations into health outcomes and connects these outcomes with associated medical expenditures and lost wages to arrive at a final cost of illness. However, it is now widely documented that this approach will underestimate the true economic cost of health damages from exposure to a pollutant. According to Freeman (2003), a 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 approach ignores these last two components. 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).

Agencies such as the U.S. EPA recognize the inadequacies of relying on a cost of illness approach. As highlighted in the agency's National Center for Environmental Economics "The practical problem [with this approach] is that unit costs for morbidity effects usually are measured in terms of avoided medical outlays and wages, which likely underestimate what people would be willing to pay to avoid the adverse health effects in question" (U.S. EPA, NCEE). For this reason, researchers have turned to the defensive, or averting, behavior method (DBM), a revealed preference approach, as well as the contingent valuation method (CVM), a stated preference approach, in an effort to monetize the true cost of damages to human health from various pollutants. While numerous studies (reviewed below) have compared estimates across two of these methods, very few have compared across all three methods common to valuing the health damages associated with exposure to a pollutant: COI, DBM and CVM.

In addition, there are various pollutants for which no studies have estimated theoretically correct willingness to pay values, meaning policy-makers must rely on lower bound cost of illness estimates in damage assessments. The U.S. EPA reports that "Even now, many important morbidity effects are poorly studied from the willingness to pay perspective. The cost of illness approach is much more common in valuing chronic illness. Consequently, benefit estimates based on a damage function approach continue to be used in many applications by EPA" (U.S. EPA, NCEE). A clear example of where this information is lacking is the health damages experienced from exposure to the pollutants released by wildfire smoke.

The Centers for Disease Control and Prevention and the U.S. EPA report that exposure to wildfire smoke can cause various ear, nose and throat symptoms as well as heightened symptoms in individuals with heart or lung disease. In addition, children and the elderly are considered sensitive populations whose health is at greater risk to be affected by exposure to wildfire smoke. Evidence of these morbidity effects has been supported by studies such as Duclos et al. (1990), CDC (1999), Johnston et al. (2002 a,b), Mott et al. (2002) Kunzli et al.(2006), CDC (2008) and others, which all find a positive correlation between wildfire smoke exposure and various adverse health effects and hospital admissions. Recent studies have called for the inclusion of their associated costs in damage assessments of a given wildfire (Butry et al., 2001; Morton et al., 2003; Abt et al., 2008; Dale, 2009). However, the costs imposed on society as a result of these potential health effects are often unknown or underestimated.

While numerous studies have applied a cost of illness approach to calculate the economic cost of health effects from wildfire smoke exposure specifically, to date, none have applied either the defensive behavior method or the contingent valuation method to calculate the willingness to pay for a reduction in associated health damages. Kochi et al. (2010) conducted a literature review on studies estimating the economic cost of health damages from wildfire smoke and one conclusion was that understanding defensive actions taken to avoid exposure to the smoke should be studied as their associated costs may be substantial.

The contribution of this study is twofold. First, using unique primary data from the largest wildfire in Los Angeles County's modern history, we apply the defensive behavior method and contingent valuation method to estimate the willingness to pay for a reduction in one wildfire smoke induced symptom day for the first time to our knowledge. Second, using the same primary data, we compare estimates across all three common approaches used to value the economic cost of health damages from a pollutant: the cost of illness approach, the defensive behavior method and the contingent valuation method. To statistically test for a significant difference in the three estimates, we apply a bootstrap resampling technique to test for overlapping confidence intervals as well as to carry out a complete combinatorial test.

The study results add to the scarce literature comparing across all three methods and provide a test of convergent validity on willingness to pay values derived from the contingent valuation and defensive behavior methods. In addition, this can help shed light on appropriate WTP: COI calibration factors for the health damages associated with wildfire smoke specifically. The remainder of this article is organized as follows: Section II provides a review of the relevant literature; Section III outlines the theoretical models motivating the analysis; Section IV discusses the sample frame and data used in the analysis; Section V presents the econometric estimation; Section VI compares values for a reduction in one wildfire smoke induced symptom day across methods; Section VII outlines conclusions and areas for future research.

II. LITERATURE REVIEW

The defensive behavior method has been used to calculate the value of a reduction in a number of air and water pollutants and the health damages associated with exposure to them, including but not limited to sulfur dioxide (Cropper, 1981; Joyce et al., 1989), nitrogen dioxide (Dickie and Gerking, 1991a), carbon monoxide (Dickie and Gerking, 1991a), ozone (Dickie et al., 1986; Gerking and Stanley, 1986; Dickie et al., 1987; Dickie and Gerking, 1991a,b) and contaminated water supplies (Harrington et al., 1989; Um et al., 2002; Dasgupta, 2004). In addition, numerous studies have applied the contingent valuation method to estimate the willingness to pay to avoid the health damages associated with various pollutants (Rowe and Chestnut, 1985; Chestnut et al., 1996; Dickie et al., 1986; Tolley et al., 1986; Berger et al., 1987; Dickie et al., 1987; Alberini and Krupnick, 2000).

A number of the above studies have also looked at the relationship between cost of illness estimates and willingness to pay values for a reduction in health effects from exposure to a pollutant and the majority of empirical findings support theoretical predictions that the cost of illness underestimates willingness to pay values. For instance, Rowe and Chestnut (1985) interviewed a panel of asthmatics in Glendora, California and found that CVM willingness to pay estimates for reductions in the severity of asthma symptoms were 1.6 to 3.7 times the comparable cost of illness estimates. Dickie and Gerking (1991b) interviewed residents in Glendora and Burbank, California and found that willingness to pay for decreased ozone levels exceeded medical expenses by a factor of two to four. Chestnut et al. (1996) found that small changes in angina frequency were associated with minor changes in costs of illness but significant changes in willingness to pay. Alberini and Krupnick (2000) estimated a WTP: COI ratio of 1.61 to 2.26 for symptoms associated with air pollution in Taiwan. Berger et al. (1987) interviewed a sample of 131 individuals in Denver and Chicago and found that for seven light health symptoms, mean daily consumer surplus estimates were always greater than mean daily cost of illness estimates, by a factor of 3.1 to 79 times. In contrast to all of these findings, Guh et al. (2008) conducted a survey in a rural area in China and found that respondents cost of illness for shigellosis, a bacterial infection caused by water contamination, actually approximated an upper bound estimate of willingness to pay to avoid the illness. The authors explain that this may be due to the fact that preventative expenditures and disutility from pain and suffering are low for this illness.

In addition, a handful of studies have studied the relationship between willingness to pay estimates derived from both the defensive behavior and contingent valuation methods, which can serve as a test of convergent validity. Dickie et al. (1986) collected data from a sample of 229 residents in the cities of Burbank and Glendora, California to implement both the contingent valuation and defensive behavior method and compared willingness to pay results across the two. The authors found that willingness to pay estimates derived from the contingent valuation method were always larger than their defensive behavior method counterparts, by a factor of up to ten times. However, a year later, Dickie et al. (1987) compiled a new data set of residents in the same cities. In this survey, respondents were asked their willingness to pay to avoid one day of recently experienced ozone related symptoms. Each bid was then multiplied by the number of times symptoms occurred in a one month period and totaled across symptoms. Respondents then had a chance to revise their bid after seeing this total. Results from this study showed that average revised bids were much lower than original bids, and revised willingness to pay estimates from the contingent valuation method were found to be smaller than their defensive behavior method counterparts. Dickie et al. (1987) explained that this result is to be expected given that defensive goods used in calculations of willingness to pay from the defensive behavior method may provide direct utility to the individuals employing them, which should lead to larger benefit estimates than those derived from the contingent valuation method. Chestnut et al. (1996) found that CVM willingness to pay estimates to avoid increases in angina were directly comparable to willingness to pay estimates based on the defensive behavior method.

As evident from the literature, there is still uncertainty on the relationship between the estimates produced by the methods commonly used to value a reduction in health effects associated with exposure to an environmental contaminant. Most importantly, very few studies have attempted to compare estimates across all three methods using the same primary data and those that have tend to compare point estimates of benefit measures. These comparisons can be made even more rigorous and accurate by evaluating statistical tests of their differences.

III. THEORETICAL FRAMEWORK

Defensive Behavior Method

As explained in previous chapters, the defensive 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). The basic idea of the defensive behavior method in this health production function framework is that if an individual experiences some health output, such as a number of days spent sick or some occurrence of symptoms, it enters into his 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. 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. A simple one period illustration is outlined as follows: an individual's utility can be expressed by:

$$U = U\ (X, L, S) \tag{4.1}$$

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:

$$S = S\ (P, A, M, Z) \tag{4.2}$$

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 are also subject to a budget constraint:

$$I + w\ [T - L - S\ (P, A, M, Z)] = X + p_A A + p_M M \tag{4.3}$$

where I represents non-labor income, w represents labor income, and the individual is assumed to allocate her total time available for work T between work, leisure and time spent sick. Averting activities have a price of $p_{A,}$ mitigating activities a price of p_M, and the price of X is normalized to 1. Therefore, the individual's utility maximization problem becomes:

$$Max\ U = U\ (X, L, S\ (P, A, M, Z)) \tag{4.4}$$

$$\text{s.t.}\ \ I + w\ [T - L - S\ (P, A, M, Z)] = X + p_A A + p_M M$$

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

$$-p_A\ /\ (\partial S/\partial A) \tag{4.5a}$$

or

$$-p_M\ /\ (\partial S/\partial M) \tag{4.5b}$$

The marginal willingness to pay 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 defensive 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 non-market good, which in this case would be a decrease in the number of symptom days experienced as a result of exposure to wildfire smoke.

Following equation (4.4) the individual can solve his dual problem of minimizing expenditures subject to a given level of utility, say u*. This expenditure minimization problem can be solved to obtain the minimum expenditure function as follows:

$$e = e\,(p_M, p_A, P, Z, S^0, u^*) \tag{4.6}$$

This is the minimum expenditure required to remain at utility level u* given sick time S^0, a set of prices, a particular pollution level and exogenous characteristics of the individual. The willingness to pay for a reduction in sick time from S^0 to S^1 can be expressed as:

$$WTP = e\,(p_M, p_A, P, Z, S^0, u^*) - e\,(p_M, p_A, P, Z, S^1, u^*) \tag{4.7}$$

This shows the maximum amount of money the individual would pay to enjoy less sick days while maintaining the same level of utility.

Cost of Illness Approach

The 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. The costs include individuals' expenditures on medical care and medications, the opportunity cost of time spent in obtaining medical care, as well as lost wages from not being able to work. This measure ignores expenditures on averting actions as well as the disutility associated with symptoms or lost leisure that will be captured in a WTP measure. From the theory underlying the defensive behavior method, we assume that mitigating activities are chosen by individuals to maximize her level of utility subject to a budget constraint. Therefore, given a particular health outcome, the decision to engage in any of these mitigating activities will likely be a function of pollution levels, prices, time spent sick, and any other exogenous factors which may influence the decision to undertake each action as follows:

$$M = M\ (p_A, p_M, P, S,^{*} Z) \qquad (4.8)$$

Once a model is estimated to control for these variables, the predicted probability that each action is taken can be multiplied by the average cost of that specific action. The sum of these values results in a final cost of illness.

Hypothesis

In this study, we compare the value of decreased morbidity from wildfire smoke based on estimates from three different estimation approaches; the cost of illness approach, the defensive behavior method, and the contingent valuation method. As explained above, theory and empirical studies consistently find that the cost of illness approach underestimates the true economic cost of health effects from exposure to various pollutants (with the exception of Guh et al, 2008). However, the expected relationship between willingness to pay values for reduced morbidity estimated by the defensive behavior and contingent valuation methods remains unclear. Therefore, the hypothesis we would like to test is as follows:

$$H_o\text{: COI} = \text{WTP}_{\text{DBM}} = \text{WTP}_{\text{CVM}}$$

$$H_a\text{: COI} < \text{WTP}_{\text{DBM}} \neq \text{WTP}_{\text{CVM}}$$

Given that these values will be calculated as either the product or ratio of two numbers, they will not have straightforward statistical properties that allow for statistical comparison of the measures. Therefore, two approaches are implemented to test this hypothesis. First, the bootstrapping method (see Efron, 1979, 1982; Efron and Tibshirani, 1993) will be applied to draw a new sample with replacement from each original dataset. This process will be repeated 1,000 times to generate a distribution of 1,000 values from each of the three methods.[13] Percentile confidence intervals will then be constructed. To do so, the distribution of values is first ordered from the lowest to the highest value and then to form, for example, the 95% confidence interval, 2.5% of the observations at each tail are dropped from the distribution. As explained in Loomis, Creel and Park (1991), while benefit estimates obtained using different valuation methods may appear to be quite different, applying simulation techniques to look for overlapping confidence intervals is a rigorous way to statistically test for a difference.

If the confidence intervals for two of the distributions of values do not overlap, it can be concluded that the null hypothesis of equality for that comparison can be rejected at the specified level of confidence. If the confidence intervals of any two distributions of values do overlap at the desired level of confidence, a second approach will be applied. Following Poe et al. (1994, 2005), we use a complete combinatorial approach based on the method of convolutions. This unbiased, nonparametric test is used to evaluate the statistical difference between two distributions by generating a third distribution consisting of all possible differences between the two distributions of interest. For instance, if comparing WTP_{DBM} with WTP_{CVM}, this third distribution is constructed by calculating $((WTP_{DBM})_i - (WTP_{CVM})_z)$ where i = 1,000 bootstrapped WTP values from the defensive behavior method and z = 1,000 bootstrapped WTP values from the

[13] While other simulation methods including the jackknife, Cameron (1991), Krinsky and Robb (1986), and delta methods could also be applied, studies comparing across methods have found that they are all relatively accurate and will produce similar results. See Cooper (1994) and Hole (2007) for these findings and an explanation of when the methods will differ.

contingent valuation method. This results in a 1,000,000 by 1 vector of differences. The proportion of negative values from this third distribution of differences represents the probability for the two willingness to pay distributions to be overlapping (if this value is greater than 0.5, it should be subtracted from 1). This probability represents the one-sided p-value associated with the hypothesis test of equality for the two distributions. Multiplying this value by two gives the two-sided p-value associated with this test. If this p-value is less than a particular level of significance, say $\alpha = 0.05$, the null hypothesis of equality of the two willingness to pay estimates can be rejected at the 0.05 significance level.

IV. SAMPLING FRAME AND DATA COLLECTION

See Chapter 2 for a complete description of the study area, survey design, data collection, and sample statistics for this study. For the contingent valuation model, only those respondents who had household members experiencing health symptoms from the Station Fire smoke were asked an additional question about their willingness to pay to reduce the health symptoms their household experienced by 50%. Before the actual question was asked, respondents were asked to take into consideration all associated costs of the illness, including the actual health effects experienced, the averting actions taken to avoid these health effects, as well as work and recreation lost as a direct result of smoke from the fire. Respondents were specifically asked not to consider any costs associated with the actual fire itself, such as damage to the home. A dichotomous choice question format was used with ten different bid amounts ranging from \$10 to \$750 based on focus groups and acute morbidity values from various studies summarized in Dickie and

Messman (2004). Table 4.1 indicates the percentage of yes responses to the willingness to pay question at each bid amount.

TABLE 4.1
Percentage of Respondents Indicating Yes to the Specified Bid Amount

Bid Amount	*N*	*Percentage Yes*
$10	22	59%
$25	21	67%
$50	18	44%
$75	18	11%
$100	14	50%
$150	12	25%
$200	7	29%
$300	11	18%
$500	19	11%
$750	15	13%

V. ECONOMETRIC ESTIMATION

Cost of Illness Model

An estimate of the cost of illness from exposure to wildfire smoke is simply the sum of expenditures made on all mitigating actions as a direct result of health symptoms experienced. While some studies have estimated econometric models of the intensity of expenditures made on these actions, we choose to model whether or not these actions were taken. Probit regression models are estimated to determine the factors that influence the probability that each mitigating action was taken, including whether or not a doctor was seen or prescription medications were taken, whether non-prescription medications were taken, whether or not work was lost and whether recreation was missed as a direct result of symptoms.[14] These mitigating action variables are regressed on all independent variables that could influence the probability that they were taken. Results of these models can be found in the Chapter 2 Appendix, Table 2.B. The total daily cost of illness is estimated by applying a formula from Alberini and Krupnick (2000) as follows:

$$\sum_M [p_M * \Phi(\bar{x} * \beta_M)] \tag{4.9}$$

where M represents each mitigating action, Φ is the standard normal cdf, x bar is the mean of the independent variables in the model, which are multiplied by their respective model coefficients, except for symptom days, which is set at 1 to reflect the daily cost of illness. The predicted probability that each action is taken is multiplied by its associated in-sample average cost reported by respondents, p_M. These are the same average costs reported in Chapter 2, Table 2.4 except for work days lost, which is adjusted to represent the lost wages from one work day lost due to health symptoms. The predicted probability is calculated by re-estimating the regression models retaining only those variables which were found to have a statistically significant effect on the probability of undertaking each mitigating activity. This is done to minimize the variance in the model and increase the precision of the estimate. Summing across all mitigating actions results in an estimate of the predicted cost of illness for the average household.

Defensive Behavior Model

To implement the defensive behavior method to calculate the mean willingness to pay for a reduction in symptom days, a health production function such as that in equation (4.2) is estimated. The health outcome experienced is the dependent variable of

[14] A model was not estimated for the mitigating action of going to a non-traditional healthcare provider given that only five individuals undertook this action.

interest, which in this case is the number of days that health symptoms were experienced as a direct result of exposure to wildfire smoke. 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.

Estimating this model has proven somewhat difficult in practice. A major complication that arises in empirical estimation, explained thoroughly by Dickie (2003) is the fact that averting and mitigating actions variables are often endogenous, jointly determined with the health outcome. These endogenous regressors will be correlated with the disturbance of the health production function equation they appear in, meaning least squares estimators will be both biased and inconsistent. Numerous studies that have estimated health production function regression 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).

The dependent variable in this analysis is count in nature (the number of days symptoms were experienced) and the potentially endogenous averting and mitigating action variables are binary, meaning nonlinear estimation techniques to address this issue of endogeneity must be employed. To estimate the health production function and address the issue of endogeneity in a nonlinear framework, we use a maximum simulated likelihood estimation procedure developed by Deb and Trivedi (2006a,b) which was explained in detail in Chapter 2, Section IV. The results of this model, including only those variables which had a statistically significant effect on expected symptom days can be found in Table 4.2. The results of this regression analysis are also explained in detail in Chapter 2, Section V.

TABLE 4.2
Defensive Behavior Model

Variable	*Coefficient*	*Robust Std. Error*
SYMPTOM DAYS - Negative Binomial Regression		
Smelled smoke indoors > 5 days	0.394***	0.142
Smelled smoke outdoors > 5 days	0.953***	0.168
Ear, nose or throat symptoms	3.630***	0.232
Breathing symptoms	0.789***	0.183
Other symptoms	0.719***	0.221
Home air cleaner	-0.848***	0.163
Hours per week of outdoor recreation	-0.023*	0.012
Male	-0.341**	0.151
Married	-0.345**	0.153
Age	0.012**	0.005
College graduate	0.479***	0.141
Employed part-time	0.625**	0.305
Lives in Duarte	0.539**	0.225
Lives in Burbank	0.460**	0.185
Lives in Glendora	0.406**	0.174
Constant	-3.701***	0.476
HOME AIR CLEANER - Probit Regression		
Smell smoke inside > 5 days	0.362	0.259
Smell smoke outside > 5 days	0.336	0.282
Ear, nose or throat symptoms	0.672***	0.242
Breathing symptoms	0.168	0.265
Other symptoms	1.374***	0.333
Hours per week of outdoor recreation	-0.017	0.021
Male	-0.183	0.246
Married	0.437	0.268
Age	-0.006	0.010
College graduate	0.375	0.248
Income	-0.005**	0.003
Employed full-time	0.560**	0.284
Employed part-time	0.519	0.461
Lives in Duarte	-0.220	0.400
Lives in Burbank	0.411	0.307
Lives in Glendora	0.496*	0.272
Believes smoke can affect health	1.426**	0.703
Constant	-3.481***	1.096
/lambda	0.858***	0.072
/lnalpha	-13.657***	2.491
N =	377	
Log Likelihood =	-672.066	
Wald chi2 (24) =	424.71	
Prob > chi2 =	0.0000001	

*: p≤0.10, **: p≤0.05, ***: p≤0.01

Contingent Valuation Model

In applying a contingent valuation framework to value a decrease in the number of symptom days experienced from exposure to a pollutant, willingness to pay will be a function of the bid amount and any variables that would enter the health production function. Freeman (2003) explains that technically you do not need to include variables other than 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. The contingent valuation portion of the survey questioned respondents about whether any members of their household experienced health symptoms from the smoke from the Station Fire. If they indicated that they had, the respondents were asked if they would be willing to pay a specified bid amount to reduce the symptoms experienced by all members of the household by 50%.

Ultimately, we would like to know the actual willingness to pay distribution of all respondents, but given the dichotomous choice question format used here, the only known information is whether a respondent responded “yes” to a specified bid amount, in which case their actual willingness to pay is greater than or equal to this value, or responded “no,” in which case their actual willingness to pay is less than this value. Thus, the actual underlying willingness to pay distribution of interest, which we refer to as WTP*, is unknown. Following closely the work of Alberini (1995), the willingness to pay model can be specified as:

$$WTP_i^* = x_i'\beta + \varepsilon \qquad (4.10)$$

where x_i' represents a vector of independent variables which could influence the individual's willingness to pay, and ε is a normally distributed error term. Whether or not an individual was willing to pay a specified bid amount is observed, so the probability that the individual responds "yes" to a specified bid amount "bid_i" is:

$$Pr\ (WTP^*_i \geq bid_i \mid x_i') = 1 - F\ (bid_i \mid x_i') \tag{4.11}$$

where F is the cumulative distribution function of WTP_i^*. This model is estimated by the method of maximum likelihood, which requires that a distribution is specified for the underlying willingness to pay. Various probability distributions were considered to model willingness to pay, however, a log-normal functional form is chosen for two main reasons. First, while a logistic distribution is frequently assumed, it has been noted that a logit regression model should have a sample size of at least 500 observations (Studenmund, 1992). However, in this study, only 157 respondents were eligible to respond to the contingent valuation question. Giraud, Loomis and Cooper (2001) cite less need for a large sample size as an advantage of the probit model over the logit model in estimating willingness to pay values. Second, assuming a non-negative distribution for willingness to pay seems reasonable for the case of valuing a decrease in symptom days from exposure to wildfire smoke. It seems implausible that individuals would hold negative values for a decrease in a health outcome whose presence is expected to reduce their utility. As Alberini and Cooper (2000) point out, a negative willingness to pay value would indicate that the average individual would actually pay to be sick. The log of the bid amount is included in the regression model to restrict willingness to pay values to lie between zero and infinity. Assuming willingness to pay follows this log-normal distribution, the probability of individual *i* responding "yes" to a specified bid amount "bid_i" becomes:

$$Pr\,(WTP^*_i \geq bid_i \mid x_i') = 1 - F(bid_i \mid x_i') = 1 - \Phi((ln(bid_i) - x_i'\beta) / \sigma) \qquad (4.12)$$

where Φ is the standard normal cumulative distribution function, and σ is the standard deviation of the log transformation of willingness to pay. Assuming $WTP_i = 1$ if the respondent is willing to pay the specified bid amount and 0 otherwise, the log likelihood function can be written as:

$$lnL = \sum_{i=1}^{n}[WTP_i * \ln\,(1 - \Phi(\frac{\ln\,(bid_i) - x_i'\beta}{\sigma}) + (1\text{-}WTP_i)\ \ln\ \Phi(\frac{\ln\,(bid_i) - x_i'\beta}{\sigma})] \quad (4.13)$$

A probit regression model is estimated to model the determinants of the predicted probability that the individual was willing to pay the specified bid amount. Additional variables added to this model include the total medical costs incurred by all household members, the total cost of averting activities taken by the household, as well as the number of people in the household who experienced symptoms. Finally, given that the respondent was valuing a 50% reduction in all symptom days experienced in the household, the duration of the illness is captured by a variable representing half of all symptom days experienced in the household. The results of this regression model, including only those variables which had a statistically significant effect on the predicted probability that the individual was willing to pay the specified bid amount can be found in Table 4.3 below. The results of the full model including all independent variables can be found in the Appendix, Table 4.A.

TABLE 4.3
Probit Regression of WTP for 50% Reduction in Symptom Days

Variable	*Coefficient*	*Std. Error*
ln (Bid amount)	-0.473***	0.097
ln (Half of household symptom days)	0.342**	0.161
Cost of averting activities	0.0006***	0.000
Times per week of exercise	-0.232*	0.141
College graduate	0.486*	0.271
Has health insurance	-1.088***	0.388
Lives in Glendora, CA	-0.596**	0.268
Constant	2.191***	0.669
N =	157	
Log Likelihood =	-75.802	
LR chi2 (7) =	51.760	
Prob > chi2 =	0.0000001	

*: $p \leq 0.10$, **: $p \leq 0.05$, ***: $p \leq 0.01$

The bid coefficient in this model is negative and statistically significant at the 1% level, meaning that the higher the bid amount, the less likely the individual was willing to pay, all else constant. This provides evidence of theoretical construct validity to the contingent valuation question responses. The natural log of half of all household symptom days is positive and statistically significant at the 5% level. The coefficient on this variable is less than one, implying that willingness to pay increases with household symptom days, but at a decreasing rate. Similarly, previous contingent valuation studies estimating the willingness to pay for symptom relief, such as Alberini et al. (1997), Johnson et al. (1997), Liu et al. (2000), and Dickie and Messman (2004), all found that the increase in willingness to pay is less than proportionate to the increase in the duration of the illness as measured by symptom days.

In addition, the more money the individual spent on averting activities, the higher the probability they were willing to pay the specified bid amount to reduce symptoms experienced in their household. This variable is significant at the 1% level and this finding is consistent with theory, which says that one of the four main components of the true value of a reduction in symptom days will be expenditures on averting activities.

Turning to lifestyle and demographic factors, similar to Liu et al. (2000) we find that exercise has a negative and statistically significant effect on the probability that the individual is willing to pay a specified bid amount, all else constant. Being a college graduate has a positive and significant effect on willingness to pay compared to those respondents without college degrees. Having health insurance has a negative effect on the probability that the individual is willing to pay the specified bid amount, and this variable is significant at the 1% level. Finally, living in the city of Glendora has a negative and significant effect on willingness to pay compared to living in Duarte, Monrovia, Sierra Madre, or Burbank.

Interestingly, a variable controlling for the number of individuals in the household who experienced symptoms was included in the full model but did not have a significant effect on willingness to pay.

VI. COMPARISON OF VALUES FOR A REDUCTION IN ONE WILDFIRE SMOKE INDUCED SYMPTOM DAY

Cost of Illness

Following equation (4.9), the predicted cost of illness for one symptom day for the average household estimated to be $9.32 as shown in Table 4.4. This cost can be viewed as conservative in that there is no assumed cost for a loss in recreation days or utility due to symptoms from exposure to the smoke from the Station Fire.

TABLE 4.4
Predicted Cost of Illness for One Symptom Day

Mitigating Action	*Predicted Probability Action is Taken*	*Average Expenditure*	*Predicted Expenditure*
Obtained medical care/prescription medications	0.0127	77.87	$0.99
Took non-prescription medicines	0.0621	16.86	$1.05
Missed work	0.0252	288.88	$7.28
Missed recreation	0.1300	N/A	N/A
Cost of Illness			**$9.32**

Defensive Behavior Method WTP

In the defensive behavior regression model, the individual willingness to pay for a given change in illness can be calculated as $[-p_a / (\partial S/\partial A)]$ from equation (4.5a). Given that using an air cleaner is the only averting action that is found to have a statistically significant and negative effect on expected symptom days, the willingness to pay measure is based on this action. The incremental effect of this endogenous input on output is -0.31, meaning the use of an air cleaner is expected to reduce symptom days by 0.31.[15] Taking the average cost reported by those respondents who used an air cleaner during the Station Fire results in an estimated price of $26.93 for this averting action. The average respondent's willingness to pay for a reduction in one symptom day from exposure to wildfire smoke is equal to -26.93/-0.31 = $86.87.

Contingent Valuation Method WTP

A goal of this study is to compare the willingness to pay value estimated by applying the defensive behavior method to the willingness to pay value estimated by applying the contingent valuation method. Therefore, the mean willingness to pay value

[15] The discrete change in expected count outcome resulting from a change in binary variable X^k from 0 to 1 can be calculated as: $[\mu_i|X^k=0][\exp(\beta^k)-1]$ where $\mu=\exp(X\beta)$, with all variables except X^k are set at their sample mean.

derived from the contingent valuation method is the statistic of interest. Given the assumed log-normal distribution of willingness to pay, this expected value can be calculated as:

$$E(WTP) = \exp(\mu + 0.5\sigma^2) \tag{4.14}$$

where μ and σ are the mean and standard deviation of the logged willingness to pay. Estimates of μ and σ are recovered as follows:

$$E\,(WTP) = \exp\left[\frac{-x_i'\beta}{\beta_{lnbid}} + 0.5\left(-\frac{1}{\beta_{lnbid}}\right)^2\right] \tag{4.15}$$

By setting all independent variables at their sample mean, we can estimate the mean willingness to pay to avoid an average number of symptom days experienced in the household. This results in a mean willingness to pay value of $339.34 to avoid an average of around seven symptom days, or $48.48 per day. Plugging in one symptom day and setting all other independent variables at their mean value results in a mean willingness to pay value of $82.82 for a reduction in one wildfire smoke induced symptom day.[16] This is the value focused on for the comparison across methods. Due to the fact that willingness to pay is increasing at a decreasing rate in symptom days, the willingness to pay to avoid one symptom day is much higher than the willingness to pay per day to avoid an average of seven symptom days. This is consistent with previous studies such as Alberini et al. (1997) who conducted a contingent valuation survey of residents in Taiwan exposed to particulate matter and ozone. The authors found that willingness to pay per day to avoid a five day illness was about one-third the willingness to pay to avoid a one day illness.

[16] One last approach would be to estimate the mean willingness to pay to move from an average of 7 symptom days to 6 symptom days. This results in a value of $35.57.

While these estimates represent the willingness to pay for a reduction in 50% of the symptom days that all members of the household experienced, recall that a covariate controlling for the number of people in the household with symptoms was included in the full regression model but was not found to be a significant determinant of the probability that the individual was willing to pay the specified bid amount (as seen in the Appendix, Table 4.A).

Comparison of Values

As expected from theoretical predictions and the majority of empirical studies, the cost of illness point estimate is considerably lower than the willingness to pay values for a reduction in one symptom day from exposure to wildfire smoke. The contingent valuation and defensive behavior willingness to pay values are around nine times larger than the cost of illness estimate, respectively. The daily willingness to pay values of $82.82 and $86.87 fall within those estimated in the literature for other air pollutants. Johnson et al. (1997) summarized a number of studies estimating willingness to pay values for a reduction in various health symptoms over the years and found that they ranged from about $5 for a reduction in one day of chest congestion up to about $194 for a reduction in one day of angina symptoms. By combining a meta-analysis of morbidity valuation studies with a health-status index, the authors themselves estimated values from $36 to $68 to avoid one day of mild cough, $110 to avoid one day of shortness of breath, and $91 to $129 to avoid one day of severe asthma.[17]

[17] All values were converted to 2009 U.S. dollars using the consumer price index

In addition, the fact that the willingness to pay value of $82.82 using a contingent valuation stated preference elicitation method is slightly smaller than the value of $86.87 which is based on a defensive behavior revealed preference elicitation method is also consistent with theory and previous findings. The defensive goods used in the defensive behavior method WTP calculation may provide a direct source of utility to the individual using them, meaning benefit estimates based on this method may be higher than their contingent valuation counterparts. In addition, Carson et al. (1996) conducted a meta-analysis consisting of 83 studies and 616 comparisons of contingent valuation (CV) and revealed preference (RP) willingness to pay estimates for quasi-public goods. They found an average sample mean CV: RP ratio of 0.89, providing evidence that contingent valuation willingness to pay estimates are on average smaller than their revealed preference willingness to pay estimate counterparts.

Given these results, it appears that the null hypothesis of equality between the cost of illness estimate and either of the willingness to pay values can be rejected, but further analysis is needed to statistically test this hypothesis. Whether the two point estimates of willingness to pay are statistically different is less clear. To explore these relationships, Table 4.5 presents the average estimates of the value for a reduction in one wildfire smoke induced symptom day, along with the 95% percentile confidence intervals around these values estimated from 1,000 bootstrapped coefficients for each of the three models.

TABLE 4.5
Values for Reduction in One Wildfire Smoke Induced Symptom Day

Method	*Point Estimate*	*95% CI*
Cost of Illness	$9.32	[$3.80-$12.78]
Defensive Behavior WTP	$86.87	[$70.99-$814.10]
Contingent Valuation WTP	$82.82	[$21.12-$1022.49]

It is clear that the 95% confidence interval of $3.80 to $12.78 around the cost of illness estimate does not overlap the 95% confidence intervals around the willingness to pay values estimated from the other two methods. As expected, the null hypothesis that the cost of illness estimate equals either of the willingness to pay values can be rejected at the 95% confidence level. Turning to the comparison of the two willingness to pay point estimates, Figure 4.1 graphically shows the lower and upper bounds of the 95% confidence interval around the two values.

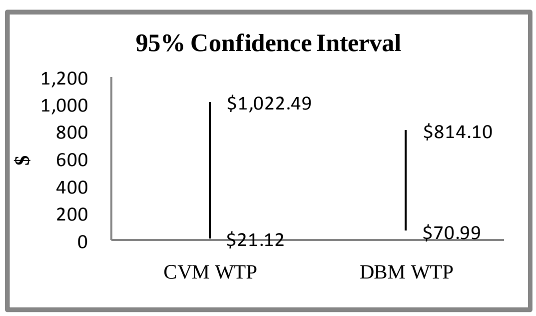

FIGURE 4.1
95% Confidence Intervals for WTP Values

The confidence interval around the willingness to pay values overlap at the 95% level of confidence, which would imply that the null hypothesis of equality between the two values cannot be rejected. However, this result should be confirmed with the complete combinatorial convolutions approach. Comparing confidence intervals to statistically test this difference has been shown to result in a higher likelihood of type II error due to overstated significance levels than the method of convolutions (Poe et al., 2005). This test results in a one-sided p-value of 0.38 and a two-sided p-value of 0.76. This confirms the comparison of confidence intervals and we conclude that the null hypothesis of equality of the two willingness to pay point estimates cannot be rejected at standard significance levels.

VII. CONCLUSIONS

There is considerable concern over the health effects individuals experience from exposure to the pollutants contained in wildfire smoke and agencies such as the U.S. EPA often attempt to quantify the cost imposed on individuals as a result of this exposure. While they realize that methods such as the cost of illness and damage function approaches ignore important components of this cost and will likely underestimate the associated economic cost of the damages to human health, they will continue to be used if there are no correct value estimates in the literature.

This study attempts to fill this gap by quantifying the theoretically correct individual value of a reduction in one wildfire smoke induced symptom day by applying two common non-market valuation approaches. Using data on the defensive actions individuals reported taking during California's Station Fire of 2009 along with their associated costs, the defensive behavior method application reveals that individuals are willing to pay an average of $86.87 for a reduction in one symptom day. Asking individuals a contingent valuation question based on a scenario about reducing half of all symptom days experienced in their households reveals that individuals are willing to pay on average $82.82 for a reduction in one symptom day. These values fall within the range found in the literature. Comparing these values to a commonly monetized cost of illness reveals that for the case of wildfire smoke, willingness to pay values can be up to nine times a cost of illness estimate. This confirms theoretical predictions that willingness to pay values incorporate significant factors that represent a loss to the affected individual but are typically ignored in estimates of monetized health damages used by agencies.

While this ratio of WTP: COI is higher than that found in the majority of previous studies which have compared the two (with the exception of Berger et al. (1987)), a few points should be noted. First, this is the only study which has calculated this ratio for the specific case of wildfire smoke using primary data. Second, this discrepancy is not surprising once the data required to implement the defensive behavior method is given a close look. For instance, while only 6.3% of survey respondents sought medical attention or took prescribed medications for symptoms, 89% took averting actions to protect themselves from exposure to the wildfire smoke. The costs of these actions would not be included in a cost of illness estimate. Further, of the 156 respondents who experienced health symptoms from exposure to the wildfire smoke, 110 of them missed recreation days as a result of these symptoms. This suggests that the disutility associated with symptoms or lost recreation captured in the willingness to pay estimate but not the cost of illness estimate may be substantial for individuals exposed to wildfire smoke.

Analysis of confidence intervals reveals that while the willingness to pay values are statistically different from the cost of illness estimate, the two willingness to pay values are not statistically different from one another as shown by the 95% confidence intervals obtained from the bootstrap method. The complete combinatorial test further confirms this finding. This result is promising for future applications of both the contingent valuation and defensive behavior method in the realm of valuation of health damages, as it provides a test of convergent validity between the two measures. While both non-market valuation techniques appear to provide a valid estimate of the health damages associated with wildfire smoke exposure, if a primary survey is being conducted, we do feel there is a considerable advantage to collecting the data needed to implement the defensive behavior method and estimate the associated health production function.

Future studies should also compare willingness to pay values to a cost of illness estimate for the specific case of wildfire smoke to test whether the ratio estimated here of nine is fairly consistent across wildfires. This could provide agencies with an estimate of the degree of inaccuracy associated with using a cost of illness estimate. Further, collecting data on attitudes about the most important components of an individual's willingness to pay for symptom reduction could be valuable. This information could confirm whether defensive actions and disutility components of symptoms and lost leisure represent a very significant economic cost to them, as suggested by the substantial difference between willingness to pay and cost of illness estimates found in this study. This information will likely become even more important in areas such as California where large wildfires are moving closer to city centers and are no longer confined to rural areas.

APPENDIX

TABLE 4.A
Full Probit Regression of WTP for 50% Reduction in Symptom Days

Variable	*Coefficient*	*Std. Error*
ln (Bid amount)	-0.573***	0.124
Smelled smoke indoors > 5 days	-0.113	0.360
Smelled smoke outdoors > 5 days	-0.060	0.399
Average daily maximum CO concentration	-0.330	1.428
Household medical costs	0.000	0.002
Cost of averting activities	0.0006*	0.000
Number of household members with symptoms	0.143	0.190
ln (Half of household symptom days)	0.354	0.268
Current respiratory condition	-0.094	0.380
Current heart condition	0.200	0.537
Past health effects from wildfire smoke	-0.029	0.333
Times per week of exercise	-0.153	0.184
Smoker	0.103	0.574
Alcoholic drinks per week	0.201	0.203
Current health is excellent	-0.366	0.584
Current health is good	0.019	0.476
Hours per week of indoor recreation	0.060	0.048
Hours per week of outdoor recreation	-0.027	0.036
Has a regular doctor	0.000	0.528
Male	-0.338	0.333
Married	0.368	0.390
Age	0.000	0.016
White	-0.124	0.380
Graduate school graduate	0.194	0.400
College graduate	0.623*	0.374
Employed full-time	-0.570	0.411
Has health insurance	-1.386***	0.522
Number of children under 18 years old in household	-0.158	0.192
Lives in Duarte	0.483	0.479
Lives in Burbank	0.189	0.415
Lives in Glendora	-0.677	0.424
Income	0.005	0.004
Heard or read about possible health effects	-0.285	0.399
Constant	2.983	2.553
N =	151	
Log Likelihood =	-65.870	
LR chi2 (33) =	65.170	
Prob > chi2 =	0.0007	

*: p≤0.10, **: p≤0.05, ***: p≤0.0

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CHAPTER FIVE

Econometric Approaches to Estimation of a Jointly Determined Health Production Function

I. INTRODUCTION

In health economics studies, the researcher is often interested in the effect of one or more treatment or choice variables on a particular health outcome of interest. Often times, estimating an econometric model to capture this effect is complicated by the fact that the treatment variable may be endogenous, correlated with the error term of the health outcome equation it appears in. For instance, it has been shown that an individual's level of health is endogenous to their demand for health care (Windmeijer and Silva, 1997); an individual's choice of health insurance is endogenous to health care utilization (Deb and Trivedi, 2006a; Hidayat and Pokhrel, 2010; Zimmer, 2010); and the advice of a physician is endogenous to the number of alcoholic drinks consumed (Kenkel and Terza, 2001), to name just a few empirical applications.

Endogeneity in econometric models stems from a variety of sources. A common cause is omitting a variable that is correlated with both an independent variable in the model as well as the dependent variable. This omitted variable is also referred to as a confounding variable. In observational data there are often many nonrandom differences across observations which cannot be directly measured. This unobserved heterogeneity is typically captured in the error term of the outcome equation; however, if it is correlated with an independent variable in the equation, it acts as a confounding variable (Zohoori and Savitz, 1997). Endogeneity may also arise due to simultaneity, where the dependent variable is affected by an independent variable, which is in turn affected by the dependent variable. Both the dependent variable and one of the independent variables are simultaneously determined, or codetermined. Other sources of endogeneity include sample selection error and measurement error, and it is possible to have numerous sources of endogeneity in one econometric model.

Correcting for the endogeneity of explanatory treatment variables is complicated in the case where the treatment variable is binary and the health outcome of interest is a count variable (takes on a nonnegative integer value) meaning nonlinear estimation techniques must be employed. This scenario is quite common in the field of health economics where the health outcome of interest may be the number of visits to a physician or the number of days spent sick and the endogenous explanatory variable is whether or not some treatment or choice was undertaken. See Windmeijer and Silva (1997), Kenkel and Terza (2001), Schellhorn (2001) and Hidayat and Pokhrel (2010) for examples. However, as explained by Winkelmann (2008) “An important example where the issue of endogeneity is a major worry is related to the effect of a (binary) treatment on a count outcome variable.”

If the endogeneity of the treatment variable is not accounted for, the coefficient estimates will be biased and inconsistent and inference can be misleading; however, correcting for binary endogenous regressors in a nonlinear framework is not always a straightforward matter. The endogenous binary treatment variable cannot be corrected for using standard two-stage instrumental variables approaches because of their nonlinear nature. While this issue of endogeneity comes up frequently in econometric applications to health, models to correct for nonlinear endogenous regressors in count data regression models may not seem readily available, making it difficult for the applied researcher to correctly address this issue. However, depending on the assumptions that are made, there are econometric approaches that the researcher can undertake.

This paper provides a guide for researchers facing this issue in empirical work. We summarize current econometric methods which can be used to address the specific challenge of estimating an econometric model with a count outcome and binary endogenous treatment variable. We present various approaches and outline the underlying assumptions, advantages and disadvantages, and empirical applications of each. These methods are then applied to estimate a health production function, where the number of days an individual spends sick as a result of exposure to wildfire smoke depends on pollution levels, various exogenous factors, as well as an endogenous binary treatment variable, specifically whether or not a home air cleaner was used to minimize exposure to the wildfire smoke. This study addresses endogeneity stemming from the common cause of unobserved heterogeneity.

In Section II we present three classes of econometric approaches that can be employed to address endogeneity in this framework; Section III presents the specific application of these approaches and comparisons across models in the context of a health production function using primary data from California's Station Fire of 2009; Section IV outlines conclusions.

II. ECONOMETRIC APPROACHES

The dependent variable in the model is assumed to take on only nonnegative integer values ($y_i = 0,1,2,\ldots$), so we start with a count data regression model. Unobserved heterogeneity is represented by specifying a multiplicative error term in addition to a random error component. An additive error term could also be specified however, the multiplicative error term treats unobserved and observed heterogeneity symmetrically, which is likely an accurate treatment if the endogeneity is assumed to stem from unobserved variables. Taking the *i*th individual from random sample I = {1…n}, this model has conditional mean:

$$y_i = E[y_i \mid x_i, d_i, l_i] = exp(x_i'\beta + \gamma d_i + ln(l_i)) + e_i = exp(x_i'\beta + \gamma d_i) l_i + e_i \qquad (5.1)$$

where x_i is a vector of observed exogenous covariates, d_i is the endogenous treatment variable, l_i is the multiplicative error term, e_i is the random error term, and β and γ are the parameter coefficients to be estimated.[18] Following Winkelmann (2008), endogeneity of the binary treatment variable d_i implies that this variable is correlated with the unobserved multiplicative error term so $E[l_i \mid d_i]$ is not a constant but rather a function of d_i. We have:

$$\text{corr}\,(d_i, l_i) \neq 0 \text{ and} \qquad (5.2)$$

$$E\,[y_i \mid x_i, d_i] \neq exp\,(x_i'\beta + \gamma d_i)$$

Ignoring the correlation between d_i and l_i and estimating a standard count data regression model such as Poisson or negative binomial would bias the estimated parameters of the model.

[18] For ease of notation, we assume a single endogenous regressor throughout.

Two Stage Estimation Approaches

The applied researcher faced with the issue of estimating an econometric model with a binary endogenous treatment variable and a count health outcome may be tempted to employ a standard two-stage instrumental variables approach. This nonlinear analogue to two-stage least squares would involve: (a) estimating a reduced form binary probability regression model (such as a probit or logit) by regressing the endogenous variable on a set of appropriate instrumental variables and all other exogenous variables in the model and (b) replacing the endogenous variable with its predicted value from this reduced form equation in the second stage nonlinear model for the count health outcome (such as a Poisson or negative binomial).[19]

However, while this approach has been widely used in empirical research, especially health economic studies (see Terza et al., 2008 for a complete list of these applications), in general it will not produce consistent results (Windmeijer and Silva, 1997; Wooldridge, 2002; Terza et al., 2008; Winkelmann, 2008). Replacing a nonlinear endogenous covariate with the predicted values from first stage estimation of the same nonlinear function in a second stage estimation has been referred to as a forbidden regression (Wooldridge, 2002).

Terza et al. (2008) refer to this method as two-stage predictor substitution (2SPS) and outline why applying this approach will typically result in inconsistent parameter estimates in a general parametric framework. To see why, it helps to start with an

[19] While there is a whole literature dedicated to what constitutes a good set of instrumental variables, they should generally satisfy three conditions: 1. They should not be correlated with the error term of the outcome equation. 2. They should be sufficiently correlated with the endogenous variable. 3. For identification purposes, there should be at least as many instrumental variables as there are endogenous covariates.

explanation of how and why two-stage least squares *does* result in consistent parameter estimates in a linear framework. Assume we begin with the following model:

$$y_i = E[y_i \mid x_i, w_i, l_i] = x_i'\beta + \gamma w_i + l_i + e_i \tag{5.3}$$

and corr $(w_i, l_i) \neq 0$

where y_i and w_i are continuous variables and the correlation between w_i and l_i is the source of endogeneity. Simple OLS would cause the error term to be (l_i+e_i) which is correlated with the endogenous variable, thus introducing bias in all estimated coefficients. To address this endogeneity in a two stage least squares framework, the first stage reduced form model would be:

$$w_i = x_i'\delta + z_i'\alpha + l_i \tag{5.4}$$

where x_i represents a vector of observed exogenous covariates in the entire system of equations, z_i represents an appropriate set of instrumental variables and l_i the random error term. OLS estimation results in residuals from this first stage regression that are uncorrelated with the endogenous variable and all other covariates in the system. Thus,

$$w_i = \widehat{w}_i + \hat{l}_i \tag{5.5}$$

The endogenous variable in the outcome equation is replaced by its predicted value from this first stage regression model, which includes a random error component (everything that affects the endogenous variable but is omitted). The second stage regression would be:

$$y_i = \hat{x}_i'\beta + \gamma\,(\widehat{w}_i + \hat{l}_i) + (l_i + e_i) \tag{5.6}$$

Since this equation is linear, this becomes:

$$y_i = \hat{x}_i'\beta + \gamma\,\widehat{w}_i + (\gamma\hat{l}_i + l_i + e_i) \tag{5.7}$$

Two stage least squares results in an additively separable error term for the outcome equation that is no longer correlated with the endogenous variable or the exogenous covariates. The endogenous variable has been purged of the influence of the outcome equation error term, the unobserved heterogeneity component l_i, resulting in unbiased and consistent coefficient estimates.

However, directly applying two stage least squares reasoning when either the outcome equation or the endogenous variable is nonlinear will typically result in biased coefficient estimates and the bias does not dissipate as the sample gets larger. For instance, if the outcome variable y_i is a count, we start with equation (5.1). As explained in Terza et al. (2008), the general problem with applying this reasoning to a nonlinear framework is that neither $\gamma\hat{l}_i$ nor l_i would be additive because they would be inside the exponential function. They could not simply be pulled out of the function to become part of the error term in the outcome equation, these error components are not additively separable like they are in the linear case.

Winkelmann (2008) outlines a very specific situation where estimation in stages may result in consistent second stage parameter estimates for the count model. This requires the strong assumptions of a recursive system of equations, a linear reduced form regression model for the endogenous variable, and full independence of the first stage residuals (l_i) and the instrumental variables ($\hat{z}_i$). These assumptions are ruled out if the endogenous variable of interest is binary (Wooldridge, 1997; Winkelmann, 2008), meaning two stage predictor substitution will never result in consistent estimates of second stage coefficients in the case of a count outcome and binary endogenous covariate.[20] See Terza et al. (2008) for a formal treatment of the consistency properties of this estimator and the degree of biasedness that can result from its application.

However, Terza et al. (2008) outline a two stage estimation approach referred to as two-stage residual inclusion (2SRI) which will provide consistent parameter estimates in a general nonlinear framework. To see why, begin with the model for a dependent count variable, y_i and endogenous binary regressor, d_i.

$$y_i = E[y_i \mid x_i, w_i, l_i] = exp(x_i'\beta + \gamma d_i + l_i) + e_i \tag{5.8}$$

and corr $(d_i, l_i) \neq 0$

Given an appropriate set of instrumental variables, the reduced form of the endogenous binary variable is as follows:

$$d_i = \Phi(x_i'\delta + z_i'\alpha) + l_i \tag{5.9}$$

where Φ is the standard normal pdf. This model can be estimated as a probit regression and the predicted value of d_i can be calculated. The residuals of this model can be defined as:

$$\hat{l}_i = d_i - \Phi(\hat{x}_i'\delta + \hat{z}_i'\alpha) \tag{5.10}$$

By maintaining the original endogenous covariate in the second stage regression and incorporating the first stage residuals from equation (5.10) the second stage becomes:

$$y_i = exp(x_i'\beta + \gamma d_i + \lambda\hat{l}_i) + e^{2SRI} \tag{5.11}$$

where e^{2SRI} is the error term from this two-stage estimator. Estimating equation (5.11) as a standard count data model will result in consistent parameter estimates given this model

[20] Another approach is to ignore the count nature of the dependent variable in the outcome equation and estimate a linear second stage with the endogenous covariate replaced with the fitted values from the first stage regression. This will result in consistent parameter estimates for the second stage even if the first stage is nonlinear (see Heckman, 1978; Dubin and McFadden, 1984; Mullahy and Portney, 1990 for examples for the specific case of a binary endogenous regressor). However, little can be said for accurate inferences in this situation.

specification. The first stage predicted residuals $\hat{l}_i$ provide a consistent estimate of the unobserved variables whose correlation with d_i was the cause of the endogeneity. Since l_i shows up directly in equation (5.8), substituting these predicted residuals in for the unobservable confounders corrects for the endogeneity and will result in consistent parameter estimates. This requires that the instrumental variables z_i' are uncorrelated with l_i. Terza et al. (2008) shows this in a general nonlinear framework and outlines the formal consistency properties of this estimator. This method has been applied in a number of studies with a nonlinear econometric framework (Burnett, 1997; Shea et al., 2007; Fang et al., 2010). Due to the two stage approach, standard errors will be underestimated and should be corrected.

However, it has been noted that the 2SRI approach may not always estimate consistent parameter estimates in the specific model that consists of a count dependent variable and binary endogenous covariate (Staub, 2009), depending on the form of the model. In Terza et al.'s (2008) specification, the first stage residuals l_i show up directly in the outcome equation (5.8), however, Wooldridge (2002) and others outline the same model with different assumptions, namely that the error term in equation (5.9) does not show up directly in equation (5.8). For instance we may have:

$$d_i = \Phi(x_i'\delta + z_i'\alpha) + v_i \tag{5.12}$$

In this case, correcting for endogeneity and estimating consistent model coefficients requires full independence of the instrumental variables z_i' and the random error term v_i (Wooldridge, 2002), a much stronger assumption than that of uncorrelatedness required in the model of Terza et al. (2008). This assumption of full independence would never be satisfied for a binary endogenous variable since any type of binary model for the endogenous covariate would produce an error term that is heteroskedastic, not fully independent of the instrumental variables. If this model is followed, any two stage approach, be it 2SPS or 2SRI, will not result in consistent estimates of second stage coefficients in the case of a count outcome variable and binary endogenous covariate.[21]

Thus, the 2SRI method may produce consistent parameter estimates for the specific case of a count dependent and binary endogenous covariate depending on what assumptions of the model are made. Regardless, the 2SRI method was originally proposed by Hausman (1978) as a means of testing for endogeneity and will still provide a valid test of endogeneity in this framework (Staub, 2009)

Nonlinear Instrumental Variables Estimation Approach (GMM)

A second approach to addressing endogeneity in a count data regression model with a binary endogenous regressor is to implement a nonlinear instrumental variables estimation approach based on the work of Mullahy (1997). Again assuming a multiplicative error term to represent the unobserved heterogeneity term that is potentially correlated with a binary covariate we have:

$$y_i = E\,[y_i \mid x_i, d_i, l_i] = exp(x_i'\beta + \gamma d_i)l_i + e_i \tag{5.13}$$

and corr $(d_i, l_i) \neq 0$

This approach requires that there exist a set of instrumental variables such that:

$$E\,[e_i \mid x_i, d_i, z_i] = 0 \text{ and} \tag{5.14}$$

$E\,[l_i \mid z_i] = 1$ (normalized to 1, the key is that it is not a function of z_i)

[21] We graciously thank Dr. Rainer Winkelmann for his assistance on clarifying this matter.

Recall, any solution to the endogeneity issue that results in consistent parameter estimates of the outcome equation will purge the endogenous variable of the influence of the outcome equation error term. Mullahy (1997) proposes a transformation of equation (5.13) to obtain a residual function where the unobserved heterogeneity term l_i is additively separable from (and thus not correlated with) the binary endogenous covariate d_i. This results in the following moment condition:

$$E[l_i \mid z_i] = 1, \text{ i.e. } E\left[\left(\frac{y_i}{exp(x_i{'}\beta + \gamma d_i)}\right) - 1 \mid z_i\right] = 0 \tag{5.15}$$

Nonlinear instrumental variables estimation techniques can then be applied to this transformed residual function to obtain consistent parameter estimates. Mullahy (1997) and Windmeijer and Silva (1997) recommend a generalized method of moments (GMM) estimator. This approach adequately corrects for the endogenous treatment variable and requires very few assumptions, only that the model has an exponential mean and there exists a strong set of instrumental variables. In addition, if there are more instruments than endogenous variables, tests for over-identification can be applied. Wooldridge (1997) explains that to implement this method, no assumptions about the distribution of the endogenous covariate given the instrumental variables, other than a standard rank condition for identification, need to be met. Thus, the researcher does not need to assume independence of the error term and the instruments in the reduced form for the endogenous variable.

This model can also be specified with an additive unobserved heterogeneity component (see Windmeijer and Silva, 1997 and Winkelmann, 2008). Windmeijer and Silva (1997) explain that when endogeneity is present, the instrumental variables used in estimation will not in general be orthogonal to both a multiplicative and additive error term specification. Determining which specification should be implemented can be tested using a standard test of overidentifying restrictions when there are more instruments than endogenous variables (Windmeijer and Silva).[22] In addition, the predicted value of the endogenous variable from a reduced form first stage binary model can be used as an additional instrument in the GMM estimation.

Applications of this approach addressing endogeneity of a continuous covariate in a count data framework include Mullahy (1997), who looks at the effect of the stock of smoking habits over time, a lagged endogenous variable, on the demand for cigarettes and estimates a birthweight production function where maternal smoking during pregnancy is assumed to be endogenous. Dickie (2005) estimates a health production function for school absences due to illness where the number of school absences and doctor visits in the past year, as well as the months since the child's last checkup and the number of children in the household, are endogenous. Other examples include Andersson et al. (2009) who estimate the effect of the number of university-based researchers on productivity and innovation in local areas.

Examples with a binary endogenous covariate and a count dependent variable include Windmeijer and Silva (1997) who estimate a model of the number of visits to a doctor in the last month which includes an endogenous binary regressor of self-reported health status, Vera-Hernández (1999) who models the demand for doctor visits where the choice of duplicate insurance coverage is endogenous and Schellhorn (2001), who looks at the effect of the choice of health insurance deductable on physician visits. Unlike two

[22] See Terza (2006) for an explanation of the potential bias that can arise from applying GMM based on a wrongly specified non-symmetric model.

stage approaches, this nonlinear instrumental variable approach is flexible enough to accommodate binary endogenous regressors in a count data model. There is a user written Stata command, *ivpois*, based on this method and written by Nichols (2007) which can be used to estimate any exponential regression model with endogenous regressor and can be specified with a multiplicative or additive error term. However, the flexibility of GMM can lead to some drawbacks such as a loss of efficiency in parameter estimates. Further, there has been a significant amount of literature on the need for a large sample size for consistent GMM estimation.

Full Information Maximum Likelihood (FIML) Approaches

Maximum Simulated Likelihood

Another econometric method which can be applied to look at the effect of an endogenous treatment variable on a count outcome of interest is a full information maximum simulated likelihood approach, based on stronger assumptions than a GMM approach. Deb and Trivedi (2006a,b) develop a joint model of count outcome and binary treatment (a special case of their multinomial treatment example) which accounts for endogeneity arising from correlated unobserved heterogeneity in the outcome and treatment equation. They generate correlated errors by incorporating latent factors into both the treatment and outcome equations, thus obtaining an appropriate joint distribution. Their model has the following outcome and treatment equations:

$$y_i{*} = x_i'\beta + \gamma d_i + \lambda l_i + e_i \tag{5.16}$$

$$d_i{*} = z_i'\alpha + \delta l_i + \eta_i \tag{5.17}$$

where x_i' is a vector of exogenous variables and d_i is the endogenous treatment variable in the outcome equation, with associated parameters β and γ. z_i' is a vector of exogenous variables in the treatment equation, with associated parameters α . The error term in each equation is partitioned into latent factors l_i and an independently distributed random error term. The latent factors represent unobserved individual specific characteristics which affect both choice of treatment and health outcome. They have associated parameters λ and δ, referred to as factor loadings. The observed random outcome variable y_i and the observed endogenous treatment variable d_i can then be modeled using appropriate distribution functions f and g as follows:

$$Pr\ [Y_i = y_i \mid x_i, d_i, l_i] = f\,(x_i'\beta + \gamma d_i + \lambda l_i) \tag{5.18}$$

$$Pr\ [d_i = 1 \mid z_i, l_i] = g\,(z_i'\alpha + \delta l_i) \tag{5.19}$$

While the random error terms, e_i and η_i are assumed to be uncorrelated, incorporating the unknown latent factors results in correlated composite error terms ($\lambda l_i + e_i$) and ($\delta l_i + \eta_i$). The joint distribution of treatment and outcome variables can then be specified as follows:

$$Pr\ [Y_i = y_i, d_i = 1 \mid x_i, z_i, l_i] = f\,(x_i'\beta + \gamma d_i + \lambda l_i) * g\,(z_i'\alpha + \delta l_i) \tag{5.20}$$

Although the latent factors l_i are unknown, the authors assume their distribution **h** is known and integrate it out of the joint density as follows:

$$Pr\ [Y_i = y_i, d_i = 1 \mid x_i, z_i] = \int [\, f\,(x_i'\beta + \gamma d_i + \lambda l_i) * g\,(z_i'\alpha + \delta l_i)] * h(l_i)\, dl_i \tag{5.21}$$

The unknown parameters of this model could be estimated by maximum likelihood. However, the integral does not have a closed form solution, so the authors apply simulation-based estimation to evaluate the integral (Gourieroux and Monfont, 1996), replacing the expectation with a simulated sample analogue such that:

$$\tilde{Pr}\,[Y_i = y_i, d_i = 1 \mid x_i, z_i] \approx \frac{1}{S}\sum_{s=1}^{S}[f\,(x_i'\beta + \gamma d_i + \lambda \tilde{l}_{is}) * g(z_i'\alpha + \delta \tilde{l}_{is})] \quad (5.22)$$

where $\tilde{Pr}$ is the simulated probability and $\tilde{l}_{is}$ is the s^{th} draw from a total of S draws of a pseudo-random number from density **h**. The simulated log-likelihood function becomes:

$$ln\, L(y_i, d_i \mid x_i, z_i) \approx \sum_{i=1}^{N} \ln\, [\frac{1}{S}\sum_{s=1}^{S}\{f(x'_i\beta + \gamma d_i + \tilde{\lambda} l_{is}) * g(z'_i\alpha + \delta \tilde{l}_{is})\}] \quad (5.23)$$

The estimator maximizes the average simulated log likelihood function, which is equivalent to maximizing the log-likelihood function if enough simulation draws are used. In order to increase the speed of simulation, the model uses quasi-random draws based on Halton sequences.

This approach is more parametric and based on stronger assumptions of maximum likelihood than the GMM approach. Full information maximum likelihood methods are also more efficient than two stage approaches and do not require adjustment of standard errors. Deb and Trivedi (2006a,b) explain the benefits of using a latent factor structure to generate correlated errors. These include being able to generate a joint distribution of treatment and outcome variables despite them not having a closed-form representation, and the ease of interpreting the factor loadings in the same way a coefficient on an observed covariate is (Deb and Trivedi, 2006a,b). The statistical significance of the coefficients on the latent factors confirms whether unobserved heteroegenity is present.

Deb and Trivedi (2006a) apply this model to estimate the effect of health insurance plan, an endogenous treatment variable, on the utilization of health care services. Deb and Seck (2009) apply it to measure the effects of migration on a wide range of variables. The downside of this approach lies in the difficulty of estimation compared to other approaches (Cameron and Trivedi, 2005). Another potential disadvantage is that the correlation between the endogenous covariate and the error term of the outcome equation due to latent factors is restricted to be less than one (Deb and Trivedi, 2006b). There is a user written Stata command *treatreg2* (Deb and Trivedi, 2006 a,b) to estimate this model. The dependent variable can be specified as negative binomial or gamma distributed with an endogenous binary treatment variable.

Endogenous Switching Models

A second full information maximum likelihood approach is the endogenous switching model, first outlined in Roy (1951) and later presented in Maddala (1983) and Amemiya (1985). Endogenous switching models are typically applied to address two common challenges in econometric models – sample selection and binary endogenous variables. The focus of this paper is on the latter, the effect of a binary treatment (regime switch variable) on a count health outcome in the presence of correlated unobserved factors which affect both treatment and outcome, i.e. the endogeneity problem. Terza (1998) and Miranda (2004) outline this full information maximum likelihood approach where a count dependent variable, y_i, is dependent on a potentially endogenous binary variable, d_i, a vector of exogenous explanatory variables, x_i, and a random error component, e_i. Assuming the model has a count outcome and following closely the work of Winkelmann (2008), the conditional mean of y_i is:

$$y_i = exp(x_i'\beta + \gamma d_i + l_i)+e_i \qquad (5.24)$$

The error term l_i represents the unobserved heterogeneity component, incorporating omitted variables. The binary treatment variable d_i is observed as follows:

$$d_i = \begin{cases} 1 \; if \; z_i{}'\alpha + v_i > 0 \\ 0 \; otherwise \end{cases} \qquad (5.25)$$

where z_i represents a set of exogenous variables with associated parameters α, and v_i is the random error term. The error terms l_i and v_i are independent of x_i and z_i but correlated with one another (thus the endogeneity). The joint conditional pdf of y_i and d_i can be specified as:

$$f(y_i, d_i \mid x_i, z_i) = f(y_i \mid d_i, x_i, z_i)\, f(d_i \mid x_i, z_i)$$

$$= \int_{-\infty}^{\infty} f(y_i \mid d_i, x_i, z_i, l_i)\, f(d_i \mid x_i, z_i, l_i)\, g(l_i) dl \qquad (5.26)$$

The joint distribution of l_i and v_i is assumed to be normal with mean 0 and covariance matrix:

$$\Sigma = \begin{pmatrix} \sigma^2 & \sigma\rho \\ \sigma\rho & 1 \end{pmatrix} \qquad (5.27)$$

The correlation parameter ρ incorporates the dependence of equations (5.24) and (5.25) and will take on a value between -1 and 1. Next, a conditional distribution needs to be specified for the outcome and treatment variables. For instance, $f(y_i \mid d_i, x_i, z_i, l_i)$ can be specified as having a Poisson distribution. We know $f(d_i \mid x_i, z_i, l_i)$ will be a binary model which is now conditional on l_i and determined by $f(l_i \mid v_i)$. Lastly, $g(l_i)$ has a normal distribution with mean 0 and variance σ^2. The joint pdf of y_i and d_i can be re-written as:

$$f(y_i, d_i \mid x_i, z_i) = \int_{-\infty}^{\infty} f(y_i \mid d_i, x_i, l_i)\, \Phi^*(l_i, z_i)^d [1 - \Phi^*(l_i, z_i)]^{1-d} g(l_i) dl \quad (5.28)$$

where $\Phi_i^*(l_i, z_i) = \Phi\left(\frac{z_i'\gamma + \rho l_i/\sigma}{\sqrt{1-\rho^2}}\right)$

The integral in equation (5.28) can be approximated using Gauss-Hermite quadrature (see Abramowitz and Stegun, 1972; Butler and Moffitt, 1982). This model is fully parametric and the log-likelihood function for sample size n is as follows:

$$\ln L = \sum_{i=1}^{n} \ln\{f(y_i, d_i \mid x_i, z_i)\} \qquad (5.29)$$

This full information maximum likelihood method allows for joint determination of the endogenous treatment and outcome variables. It is based on information about the entire system of equations, and given normally distributed error terms, full information maximum likelihood will be efficient among all estimators (Greene, 2003 p. 407). The drawback of this approach is again the burden of estimation (Terza, 1998). However, with increased computing power this is no longer such a problem. Applications of endogenous switching models can be found in Kenkel and Terza (2001) and Schellhorn (2002). Miranda (2004) has written a Stata command, *espoisson*, which will estimate this model assuming a Poisson distribution for the outcome variable.

Other Approaches

Other approaches to addressing endogeneity of a binary variable in a count data model which will not be applied in this study include a two-stage pseudo-likelihood approach where the binary endogenous covariate is assumed to be some proxy for an unobserved continuous latent variable (see Heckman, 1978; Windmiejer and Silva, 1997). In addition, Terza (1998) implements a two-stage method of moments and a nonlinear weighted least squares procedure which are both also applied in Schellhorn (2002). Further, the endogeneity could arise due to sample selection in addition to unobserved heterogeneity. While this paper does not go into detail about potential remedies in this situation, see Bratti and Miranda (2010) for a good discussion on methods to address both types of endogeneity simultaneously.

III. EMPIRICAL APPLICATION: ESTIMATION OF A HEALTH PRODUCTION FUNCTION

Theoretical Model

Beginning with the work of Grossman (1972), there is a widely accepted notion in the field of health economics that individuals act as "producers" of their own good health. While a negative health outcome is assumed to enter an individual's utility function directly, this outcome is often not exogenous, but rather depends in part on the investments of time and money individuals make in activities that can affect its production. This health production framework provides a basis for the defensive behavior method, a revealed preference approach often used in the field of non-market valuation to infer the individual value of a reduction in the health symptoms that result from exposure to an environmental contaminant. To derive this value, the researcher needs to estimate a health production function as follows:

$$S = S\,(P, D, Z) \tag{5.30}$$

The negative health output S is often modeled as the number of days an individual spends sick and is a function of pollution levels P, exogenous factors that could affect the time spent sick such as the individual's stock of health, lifestyle factors and demographic factors Z, as well as any defensive actions taken by the individual to decrease this time spent sick D. Defensive actions include those that are taken to decrease the chance of being exposed to some pollutant that causes the negative health outcome or the health outcome itself, such as staying indoors or using an air cleaner in the home, as well as those 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. It can be assumed that sick time is increasing in exposure to the pollutant and decreasing in defensive actions. The researcher is often interested in calculating the individual willingness to pay for a reduction in time spent sick, which can be calculated as follows:

$$-p_D / (\partial S/\partial D) \tag{5.31}$$

The marginal value of reduced time spent sick is equivalent to the price of any defensive action divided by the marginal effect of the use of that defensive action on symptom days.

The main econometric challenge to estimating this model lies in the potential endogeneity of the defensive action variables. As explained by Dickie (2003, p.425) "Unobserved factors affecting health outcomes will be correlated with unobserved factors affecting choices of health input. Ignoring this simultaneity results in biased and inconsistent estimators of parameters of the health production function." Numerous studies estimating health production functions in the context of the defensive behavior method 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).

Data and Econometric Model

A survey of residents exposed to unhealthy levels of air quality during California's Station Fire of 2009 provided the data for this study. We refer the reader to Chapter 2 for a complete description of the study area, survey design, data collection, and sample statistics for this study. The negative health outcome experienced is modeled as the number of symptom days experienced as a direct result of exposure to the wildfire smoke, which is a count variable. The defensive action variable is modeled as a binary variable, leading to the following model specification:

$$y_i = E[y_i \mid x_{i,} w_{i,} l_i] = exp(x_i{'}\beta + \gamma d_i + l_i) + e_i \qquad (5.32)$$

$$\text{and corr } (d_i, l_i) \neq 0$$

where y_i is the number of symptom days experienced, d_i is the potentially endogenous binary defensive action covariate, and x_i' is a vector of all exogenous variables which could affect the number of symptom days experienced.

Preliminary analyses of the data indicate a few things. First, the mean of the dependent variable is 3.28 and the variance is 36.67, meaning the raw data suffers from over-dispersion. The presence of over-dispersion is confirmed by comparing the log-likelihood from both a Poisson and negative binomial model. A likelihood-ratio chi-square test is used to test whether the dispersion parameter is equal to zero. This test statistic has a value of 157.26 and is statistically significant at the 1% level, suggesting that over-dispersion is present.

Second, the only defensive action variable that has a negative and statistically significant effect on the number of symptom days experienced is using a home air cleaner, a potentially endogenous variable. There are possible unobserved factors that partially affect the choice to use a home air cleaner and simultaneously affect the occurrence of symptom days resulting from exposure to the wildfire smoke, meaning the choice to use a home air cleaner is likely correlated with the error term of the symptom day equation. This unobserved heterogeneity may cause positive or negative correlation and could reflect un-captured effects such as risk preferences or possibly some predisposition to getting sick. For instance, those individuals who are more risk-averse or may have more experience with wildfires could be more likely to use an air cleaner to minimize exposure to the wildfire smoke but in addition, they may take *many* precautions that are not captured in the model, causing them to also experience less symptom days. This would reflect negative correlation. On the other hand, there may be unobservable factors that increase the likelihood of using a home air cleaner and simultaneously increase the number of symptom days experienced. This could reflect some underlying and un-captured predisposition to getting sick. If individuals know that they tend to experience health effects when exposed to a pollutant like wildfire smoke, they may be more inclined to use a home air cleaner to prevent this but may also be more likely to experience a greater number of symptom days. Therefore, it is not clear whether estimates of the partial effect of using an air cleaner on symptom days will be biased upward or downward in the health production function if the endogeneity of this choice variable is not accounted for. The data used to estimate the health production function can be found in Table 5.1.

TABLE 5.1
Variables and Summary Statistics

Variable	Coding	Mean	Std. Dev.	Min	Max
Pollution Levels					
Days smoke smelled outdoors	3=1-5 days; 8=6-10 days; 13=11-15 days; 16=more than 15 days	7.77	4.91	0	16
Days smoke smelled indoors	3=1-5 days; 8=6-10 days; 13=11-15 days; 16=more than 15 days	3.43	4.21	0	16
Illness Information					
Symptom days	count	3.28	6.06	0	45
Ear, nose or throat symptoms	1= yes, 0= no	0.36	0.48	0	1
Breathing Symptoms	1= yes, 0= no	0.18	0.39	0	1
Heart Symptoms	1= yes, 0= no	0.04	0.20	0	1
Other symptoms	1= yes, 0= no	0.09	0.28	0	1
Health History					
Current respiratory condition	1= yes, 0= no	0.12	0.32	0	1
Experienced health effects from wildfire smoke in past	1= yes, 0= no	0.24	0.42	0	1
Health and Lifestyle					
Hours per week of outdoor recreation	continuous	4.95	7.11	0	77
Demographics					
Male	1=male, 0=female	0.60	0.49	0	1
Married	1=yes, o=no	0.69	0.46	0	1
Age	continuous	59.11	15.37	24	94
Graduate school graduate	1= yes, 0= no	0.20	0.40	0	1
College graduate	1= yes, 0= no	0.62	0.49	0	1
Employed part-time	1= yes, 0= no	0.08	0.27	0	1
Lives in Duarte	1= yes, 0= no	0.13	0.34	0	1
Lives in Burbank	1= yes, 0= no	0.19	0.40	0	1
Lives in Glendora	1= yes, 0= no	0.40	0.49	0	1
Defensive Action					
Home air cleaner	1= yes, 0= no	0.21	0.41	0	1

Choice of Instrumental Variables

To test for the endogeneity of using a home air cleaner, as well as to implement many of the econometric remedies, there first needs to exist a set of appropriate instrumental variables that directly affect the decision to use a home air cleaner, but do not directly affect the number of symptom days experienced. The choice of these variables is somewhat subjective, but Dickie (2003) recommends variables such as wage, income, prices of defensive activities, and other demographic or attitudinal variables that could affect the decision to undertake a defensive action. Five variables are found to be potentially sufficient instrumental variables in this framework and are outlined in Table 5.2.

TABLE 5.2
Potential Instrumental Variables for the Reduced Form Probit Model

Variable	**Coding**
Believes that smoke can affect health	1= yes, 0= no
Believes that defensive actions are effective at reducing health effects	1= yes, 0= no
Heard or read about health effects of wildfire smoke	1= yes, 0= no
Income	continuous
Employed full-time	1= yes, 0= no

The potentially endogenous variable "Home air cleaner" is regressed on all exogenous variables in the system, as well as the five potential instrumental variables in a probit regression model. Instrumental variables should be sufficiently correlated with the endogenous variable but orthogonal to the error process of the outcome equation. To test the first requirement, t-tests of statistical significance as well as an F-test of the joint significance of the potential instrumental variables can be implemented. A good rule of thumb is that for a single endogenous regressor, an F test statistic on the instrumental variable coefficients of less than ten signifies the presence of weak instruments (Staiger and Stock, 1997; Stock and Yogo, 2005). Four of the five potential instrumental variables (all but "Heard or read about health effects of wildfire smoke") are found to be individually significant in determining the predicted probability of "Home air cleaner" at standard significance levels. A likelihood ratio test of the joint significance of these four instruments is 13.43 with a p-value of 0.009, indicating that weak identification is not an issue.[23]

Testing whether the instrumental variables are orthogonal to the error process can be done if the model is over-identified. This test is referred to as the J statistic of Hansen (1982) in a GMM framework and based on Sargan (1958) in an instrumental variable framework. An informal test of this requirement is to regress the dependent variable "Symptom days" on all exogenous variables including the excluded instrumental variables and test the joint significance of the instrumental variables. This results in a likelihood ratio test statistic of the joint significance of these variables of 2.91 with a p-value of 0.57, with none being individually significant. This test indicates that while these instrumental variables directly affect the use of a home air cleaner, they do not directly affect the expected number of symptom days experienced and thus they make good instruments.

Results

The results of a negative binomial model uncorrected for endogeneity, the two-stage predictor substitution and two-stage residual inclusion models, the generalized

[23] It should be noted that the presence of weak identification can result in biased parameter estimates (Bound et al., 1995; Staiger and Stock, 1997)

method of moments instrumental variable estimator, and the two FIML techniques including the maximum simulated likelihood and endogenous switching models, are shown in Table 5.3. Standard errors were adjusted by bootstrapping for the two stage approaches. For the maximum simulated likelihood model, two thousand simulation draws were used based on recommendations from Deb and Trivedi (2006a) and robust standard errors which take simulation error into account are reported. For the endogenous switching model, forty quadrature points were used in the numerical approximation of the integral, as allowing for more did not change the log likelihood or estimated parameters.

The negative binomial model 1, uncorrected for potential endogeneity of using a home air cleaner, results in a positive coefficient on “Home air cleaner.” However, this variable does not have an actual effect on expected symptom days in this model as its coefficient is not significant at standard significance levels with a p-value of 0.407. In the two-stage predictor substitution model 2, which includes the predicted value of “Home air cleaner” but has been shown to be inconsistent in a general nonlinear framework (Terza et al., 2008), the sign on “Home air cleaner” changes to a negative with a coefficient of -1.138 but this variable has a p-value of 0.112 so it is not quite significant at the 10% level.

TABLE 5.3
Health Production Function Estimates for Number of Symptom Days

Variable	Model 1 *Negative Binomial*	Model 2 *2SPS*	Model 3 *2SRI*	Model 4 *GMM*	Model 5 *Maximum Simulated Likelihood*[b]	Model 6 *Endogenous Switching*[c]
Constant	-3.333***	-3.27***	-3.277***	-3.359***	-3.627***	-3.608***
(standard error)	(0.392)	(0.565)	(0.581)	(0.394)	(0.549)	(0.437)
Days smoke smelled outdoors	0.082***	0.091***	0.093***	0.088***	0.094***	0.098***
	(0.014)	(0.020)	(0.018)	(0.018)	(0.014)	(0.016)
Days smoke smelled indoors	0.018	0.028*	0.027*	0.029**	0.024	0.028*
	(0.014)	(0.015)	(0.014)	(0.014)	(0.020)	(0.016)
Ear, nose or throat symptoms	3.201***	3.290***	3.285***	2.917***	3.487***	3.439***
	(0.177)	(0.362)	(0.326)	(0.405)	(0.310)	(0.211)
Breathing symptoms	0.856***	0.840***	0.831***	0.569***	0.705***	0.728***
	-(0.141)	-(0.212)	-(0.215)	-(0.153)	-(0.183)	-(0.156)
Other symptoms	0.303*	0.711**	0.739**	0.443*	0.564**	0.619***
	(0.163)	(0.338)	(0.313)	(0.264)	(0.270)	(0.189)
Current respiratory condition	-0.267	-0.290	-0.270	-0.202	0.041	-0.189
	(0.166)	(0.205)	(0.200)	(0.146)	(0.154)	(0.174)
Experienced health effects from wildfire smoke in past	0.200	0.284	0.277	0.132	0.180	0.234
	(0.132)	(0.193)	(0.195)	(0.120)	(0.213)	(0.151)
Hours per week of outdoor recreation	-0.033***	-0.037**	-0.037***	-0.010	-0.030**	-0.027**
	(0.012)	(0.014)	(0.015)	(0.010)	(0.014)	(0.012)
Male	-0.321**	-0.367**	-0.358**	-0.248	-0.329**	-0.391**
	(0.142)	(0.166)	(0.170)	(0.175)	(0.154)	(0.153)
Married	-0.430***	-0.348**	-0.328**	-0.400***	-0.362**	-0.279*
	(0.139)	(0.167)	(0.156)	(0.121)	(0.157)	(0.156)
Age	0.014***	0.013**	0.013**	0.018***	0.012**	0.012**
	(0.004)	(0.006)	(0.006)	(0.004)	(0.006)	(0.005)
Graduate school graduate	-0.264*	-0.223	-0.204	-0.135	-0.204	-0.196
	(0.155)	(0.176)	(0.166)	(0.133)	(0.156)	(0.170)
College graduate	0.488***	0.509***	0.510***	0.526***	0.471***	0.489***
	(0.143)	(0.168)	(0.174)	(0.158)	(0.159)	(0.154)
Employed part-time	0.547**	0.590	0.597	0.322	0.494	0.460*
	(0.224)	(0.392)	(0.390)	(0.215)	(0.486)	(0.262)
Lives in Duarte	0.493***	0.450	0.450	0.102	0.399*	0.306
	(0.190)	(0.292)	(0.292)	(0.297)	(0.217)	(0.218)
Lives in Glendora	0.281*	0.434**	0.424**	0.305*	0.346*	0.357**
	(0.152)	(0.176)	(0.188)	(0.165)	(0.178)	(0.168)
Lives in Burbank	0.207	0.363**	0.368**	0.360**	0.338**	0.357**
	(0.167)	(0.183)	(0.191)	(0.169)	(0.166)	(0.181)
Home air cleaner[a]	0.108	-1.138	-1.215*	-0.404	-0.729***	-0.960***
	(0.130)	(0.716)	(0.682)	(0.617)	(0.169)	(0.273)
Home air cleaner residuals			1.414**			
			(0.703)			
N =	402	376	376	376	376	376
Log Likelihood	-522.96	-506.27	-505.19		-653.25	-653.29
lamda (latent factor)					0.757***	
lnalpha					-13.589**	
sigma						0.787***
rho						0.833***

[a] - potentially endogenous variable

[b] - estimated using Stata 11.0 command treatreg2 (Deb and Trivedi, 2006b)

[c] - estimated using Stata 11.0 command espoisson (Miranda, 2004)

*: p≤0.10, **: p≤0.05, ***: p≤0.01

The two-stage residual inclusion estimation procedure may result in consistent parameter estimates depending on how the unobserved heterogeneity enters the system of equations, as described in Section II. However, it will definitely provide a consistent and relatively simple test of endogeneity in this nonlinear framework (Staub, 2009). If the included residuals of the reduced form equation for the endogenous variable are significant, this is an indication of the presence of endogeneity of that variable. The coefficient on "Home air cleaner" in model 3 has a p-value of 0.075 and the coefficient on the residual has a p-value of 0.044. Thus, while it appears that the variable is endogenous, it is significant at only the 10% level. A Hausman specification test if carried out to further test whether "Home air cleaner" is endogenous by comparing the coefficients of the uncorrected negative binomial model 1 with those of the two-stage residual inclusion model 3. The null hypothesis of this test is that both estimators are consistent but only the uncorrected negative binomial model is efficient. This results in a test statistic, distributed chi-square, of 93.52, with a p-value of 0.00001, confirming that endogeneity is present and the uncorrected model is inconsistent.

The two-step generalized method of moments nonlinear instrumental variables model 4 results in a negative but insignificant coefficient on the endogenous variable. The Hansen J test for over-identifying restrictions tests for correct model specification as well as the othogonality conditions. Rejecting the null hypothesis implies that the instrumental variables do not satisfy the orthogonality conditions necessary for their use (Baum et al., 2002). This results in a test statistic of 3.34 (p-value of 0.34) in the additive model and 13.40 (p-value of 0.004) in the multiplicative model, indicating that the set of instruments used are appropriate for the former and not the latter. Therefore, model 4 represents the additive specification. This test statistic indicates that the null hypothesis that all instrumental variables are uncorrelated with the error term cannot be rejected at standard significance levels. The lack of significance of the endogenous variable “Home air cleaner” in this model is a consequence of the larger standard errors produced by this estimation procedure. Recall, this model specifies very few assumptions about the distribution of the data, and therefore, there will be a loss of efficiency and less precise parameter estimates. In addition, there is also a tendency for two-step GMM to perform poorly in small samples (Altonji and Segal, 1996; Wooldridge, 2001; Cameron and Trivedi 2005), which could also cause misleading results.

In the two full information maximum likelihood models “Home air cleaner” is negative and statistically significant at the 1% level. In model 5, the positive and statistically significant coefficient on the latent factor, lambda, indicates that individuals who are more likely to use an air cleaner, based on unobserved characteristics, are also more likely to experience symptom days. This coefficient is valuable in that it confirms the presence and the direction of the unobserved heterogeneity. This explains why failing to account for the unobserved heterogeneity in model 1 makes it appear that using a home air cleaner has a positive effect on the expected number of symptom days. Once the underlying latent factors in both the outcome and treatment equation are accounted for, the accurate effect of using a home air cleaner on the expected number of symptom days becomes clear. This allows accurate measurement of the impact of those who use an air cleaner and those who don’t on sick days. It is quite common for the sign of the potentially endogenous variable to switch once the bias is corrected for (see Vera-Hernández, 1999; Kenkel and Terza, 2001).

In the endogenous switching model 6, the statistical significance of the coefficients on sigma and rho indicate the presence of unobserved heterogeneity and thus support for the endogenous switching estimation procedure. It is also relatively easy to compare these results to an exogenous switching model, which can be found in the Appendix, Table 5.A. The coefficient on "Home air cleaner" changes considerably in the two model specifications and the endogenous specification results in a slightly smaller AIC value, suggesting superiority of the endogenous switching model over the exogenous switching model. It should be noted that this model is estimated with the Stata command *espoisson*, which assumes the dependent variable "Symptom days" is Poisson distributed, for comparison purposes. However, as mentioned previously, the data appears to suffer from over-dispersion, which can result in overstated significance levels.

When applying the defensive behavior method to value a marginal reduction in symptom days using equation (5.31), the researcher needs to calculate the marginal effect of the use of the defensive action variable on expected symptom days. Since these models assume the dependent variable has an exponential mean, the discrete change in expected count outcome resulting from a change in a binary variable X^k from 0 to 1 can be calculated as: $[\mu_i|X^k=0][\exp(\beta^k)-1]$ where $\mu=\exp(X\beta)$, with all variables except X^k set at their sample mean. Dividing the full price of the defensive action variable by this marginal effect gives the resulting willingness to pay value for a reduction in one symptom day. Taking the average of the in-sample reported cost of those individuals who used a home air cleaner results in a price of $26.93 for this defensive action. The marginal effect of using a home air cleaner on expected symptom days is calculated for each model and the resulting willingness to pay value for a reduction in one symptom day is calculated for only those marginal effects which were significant at standard significance levels. These values are shown in Table 5.4 below. As can be seen, the marginal effects vary depending on the chosen model. The negative binomial model uncorrected for endogeneity of this variable results in a positive marginal effect. The 2SPS and 2SRI models result in smaller (more negative) marginal effects than the GMM and FIML models, and thus smaller willingness to pay values. The two FIML models and the GMM estimator have similar marginal effects. Thus, it appears that the choice of model used to correct for the endogeneity of the defensive action variable can make a large difference for policy recommendations. Figure 5.1 visually shows the 95% confidence intervals around the marginal effects for each econometric model.

TABLE 5.4
Marginal Effect of Air Cleaner Use on Expected Symptom Days

	Marginal Effect	Willingness to Pay
Negative Binomial	0.067	
2SPS	-0.547	
2SRI	-0.584**	$46
GMM	-0.265	
Maximum Simulated Likelihood	-0.283***	$95
Enodgenous Switching	-0.275***	$98

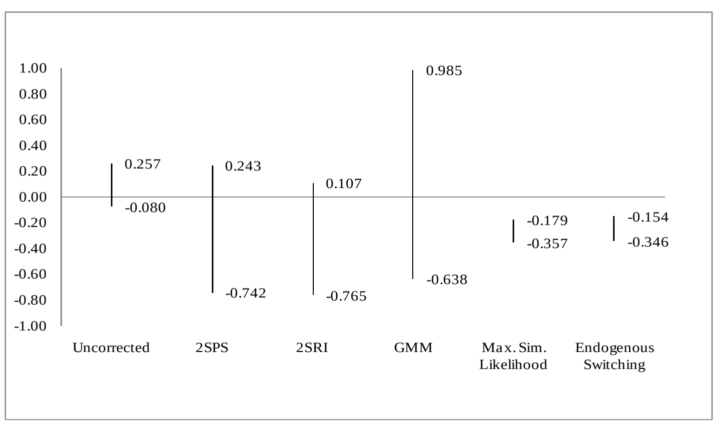

FIGURE 5.1
95% Confidence Intervals for Marginal Effects

Comparison of Models

In comparing results across model specifications, there are some considerable differences that should be noted. First, failing to correct for the endogeneity of "Home air cleaner" results in serious bias in the estimated coefficients, as evident by the positive (but insignificant) coefficient on this variable in the negative binomial model. While it has been shown that a two-stage predictor substitution method will in general not result in consistent parameter estimates in a nonlinear framework, two-stage approaches such as two-stage residual inclusion can produce consistent parameter estimates in many nonlinear models (Terza et al., 2008). In addition, this approach allows for simple testing of the endogeneity of variables, even in the case of a count dependent variable with potentially endogenous binary covariates. However, a major drawback to two-stage remedies to endogeneity lies in the loss of efficiency in the parameter estimates, as evident by the considerably larger standard error on "Home air cleaner" in Table 5.3. In addition, given the very large difference in the marginal effect produced by the 2SRI model compared to the two FIML models, further research should be done to test whether this model is appropriate for the specific case of a count dependent variable and binary endogenous covariate.

Generalized method of moments' approaches to addressing endogeneity in a nonlinear framework have gained considerable popularity and can be quite desirable in that the researcher does not need to impose hardly any distributional assumptions to obtain a consistent estimator. The estimator used here just assumed that the dependent variable had an exponential mean. This estimator is also desirable in that it can handle multiple endogenous regressors, of any distributional form, and easily implements tests of over-identifying restrictions. However, the lack of information used in estimation will result in a loss of precision in the estimated coefficients, especially of the endogenous variable of interest, which has been found in other empirical applications (Windmeijer and Silva, 1997; Schellhorn, 2002). Another drawback of this approach is that the endogenous variable of interest is not modeled separately.

The full information maximum likelihood approaches are more parametric than the GMM procedure and require the imposition of greater distributional assumptions about the data, but the result is considerable gains in efficiency. Both the maximum simulated likelihood model and the endogenous switching model allow for correlated error terms of the endogenous and dependent variable in the model specification and jointly estimate both equations in the system. Both of these models are identified through functional form, which means no additional instrumental variables are necessary for identification, although it is recommended to include at least one. Table 5.3 shows that the endogenous variable “Home air cleaner” in these two models has a negative and significant effect on the expected number of symptoms days. This indicates that there are not only efficiency, but also information gains to using a full information maximum likelihood estimation procedure. These methods are also very robust to changes in instrumental variables. Finally, these two approaches produced very similar marginal effects of the defensive action variable on expected symptom days and thus willingness to pay values, even though one assumed a negative binomial distribution for the dependent variable and the other a Poisson distribution.

IV. CONCLUSIONS

This study has looked at econometric methods used to address the endogeneity of a binary choice variable in a count data regression model. It is shown both theoretically and empirically the bias in parameter estimates that can result from ignoring the endogeneity of covariates. Results from this study indicate that a two-stage residual inclusion approach may not result in consistent parameter estimates for the specific case of a count data regression model with a binary endogenous covariate. However, this approach will provide a simple test of endogeneity in this nonlinear framework. A generalized method of moments' estimator was also implemented, which can be specified with an additive or multiplicative error term and provides a useful approach if the researcher is unsure of the exact distribution of the outcome or endogenous variable and may be best applied with a large sample size. While two-stage residual inclusion and generalized method of moments' approaches can achieve consistent parameter estimates, they will nonetheless result in a loss of efficiency compared to standard maximum likelihood approaches.

By imposing additional distributional assumptions about the data at hand, full information maximum likelihood methods will achieve the statistically most efficient estimator (Miranda, 2004). These methods may also be desirable with a relatively small sample size as they utilize all the information given and result in more precise parameter estimates than two-stage residual inclusion or generalized method of moments' approaches. While the burden of estimation due to lack of computing power has prevented use of these methods in the past, this is no longer a problem. This study looked at two full information maximum likelihood estimation procedures, both of which have user-written Stata programs that make them simple to implement. If the dependent variable is Poisson distributed, we recommend the simple *espoisson* Stata command and if it has a negative binomial or gamma distribution, we recommend the *treatreg2* command. These models also provide coefficient estimates which confirm the presence of unobserved heterogeneity.

Depending on the distributional assumptions that the researcher is comfortable making, sample size, and the desired efficiency of parameter estimates, there are a variety of estimation approaches to address endogeneity of a binary regressor in count data models. However, the choice of model used to address this endogeneity should be given considerable attention, as policy recommendations may change substantially depending on which is estimated. While this study looked at one sample of data, future studies could compare across models using Monte Carlo simulation to gain greater insight into model differences for varying sample sizes.

APPENDIX

TABLE 5.A
Exogenous Switching Model

Variable	*Coefficient*	*Std. Error*
Constant	-3.767***	0.421
Days smoke smelled outdoors	0.091***	0.015
Days smoke smelled indoors	0.021	0.015
Ear, nose or throat symptoms	3.333***	0.207
Breathing symptoms	0.755***	0.141
Other symptoms	0.307*	0.163
Current respiratory condition	-0.200	0.165
Experienced health effects from wildfire smoke in past	0.189	0.139
Hours per week of outdoor recreation	-0.028**	0.012
Male	-0.308**	0.146
Married	-0.431***	0.146
Age	0.016***	0.004
Graduate school graduate	-0.256	0.164
College graduate	0.467***	0.148
Employed part-time	0.496**	0.233
Lives in Duarte	0.390*	0.205
Lives in Glendora	0.31*	0.159
Lives in Burbank	0.290	0.177
Home air cleaner[a]	0.030	0.140
N =	376	
Log Likelihood	-656.260	
Wald chi^2	460.630	
Prob > chi^2	0.000001	
sigma	-0.451***	

[a] - potentially endogenous variable

*: p≤0.10, **: p≤0.05, ***: p≤0.01

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CHAPTER SIX

Concluding Remarks

This study sought to monetize the full economic cost of health effects from exposure to wildfire smoke using theoretically correct non-market valuation techniques. Data from a mail survey of residents exposed to smoke from California's Station Fire of 2009 indicates that individuals do indeed experience a range of health effects from wildfire smoke and while a small percentage sought medical care as a result of these damages, a large portion, 89% in this sample, took preventative actions to defend themselves from this exposure. As a result, the defensive behavior method is found to be applicable in the case of wildfire smoke exposure. We find that on average, the expenditures individuals make on actions taken to defend themselves from exposure to wildfire smoke are larger than the medical costs and lost wages that a commonly reported cost of illness estimate consists of.

As explained by Freeman (2003), a pollutant that affects human health impacts well-being in four ways: incurred medical expenses and lost wages (the sum of which is the cost of illness), expenditures on averting activities taken to avoid the health effects, and the disutility associated with symptoms or lost leisure. The true value of a reduction in a pollutant or the associated health symptoms should consist of all four of these components. This study attempted to measure as many of these components as possible for the specific case of reductions in unhealthy levels of air quality produced by wildfire smoke. Specifically, by applying the defensive behavior method we measure the willingness to pay for a reduction in perceived pollution levels as measured by the number of days wildfire smoke was smelled indoors. Table 6.1 decomposes willingness to pay values for avoiding 1-5 days of wildfire smoke and avoiding greater than five days of wildfire smoke into the various components that make up this value.

TABLE 6.1
Components of Willingness to Pay for Decreased Pollution (DBM)

Value of Avoiding 1-5 Smoky Days		**Value of Avoiding > 5 Smoky Days**	
Cost of illness	11.34	Cost of illness	11.34
Averting expenditures	+24.53	Averting expenditures	+54.89
Value of disutility	+24.78	Value of disutility	+39.77
Willingness to pay	60.65	Willingness to pay	106.00

While the value of reduced pollution levels is an interesting measure, it is often less policy relevant than the value of reduced symptom days from exposure to a pollutant. A health production function used to implement the defensive behavior method is estimated and shows that factors such as the number of days wildfire smoke was smelled inside or outside the home as well as using an air cleaner in the home are important determinants of the number of symptom days experienced. Information on the defensive actions individuals took during the wildfire along with the associated expenditures on market goods was used to infer the value of a reduction in one wildfire smoke induced symptom day. This is calculated to be $86.87. While endogeneity in a nonlinear framework is a common challenge to estimating health production functions for the defensive behavior method, this study explored a variety of econometric approaches to address the specific case of a binary endogenous regressor in a count data model.

Responses to a contingent valuation question were also used to infer the value of a reduction in one wildfire smoke induced symptom day, which is estimated to be $82.82. Statistical tests comparing these two willingness to pay values indicate that they are not statistically different, providing a test of convergent validity between the two methods. Comparing these values to a simple daily cost of illness estimate reveals that the WTP: COI ratio of about two often used in the literature for the specific case of health damages from wildfire smoke exposure may be inaccurate. We estimate this ratio to be much higher at around nine to one.

This information on appropriate calibration factors may be valuable to agencies and policy makers who are interested in capturing the full economic cost of health damages from exposure to wildfire smoke but have access to simple cost of illness estimates only. In addition, when evaluating fire prevention programs, an accurate analysis would require inclusion of the economic cost of human health damages from a wildfire that could be prevented by implementing these programs. Omitting these health benefits of fire prevention programs in a benefit cost analysis of such programs would result in too small an investment in prevention measures such as prescribed burns or forest thinning. There will undoubtedly be uncertainty surrounding the nature of fires that "could have been." However, if agencies could estimate certain components of the avoided wildfires resulting from prevention, such as size, intensity, and the number of people that would have potentially been affected, they could determine whether the Station Fire used in this study is an appropriate representation. They could then multiply the willingness to pay value for a reduction in one symptom day from wildfire smoke exposure obtained in this study by the average number of symptom days experienced and the number of individuals that would have been affected to arrive at an estimate of the cost of health damages avoided by the prevention measure. Further, as more willingness to pay estimates become available in the literature, these benefit transfer practices can become increasingly accurate.

In conclusion, this study adds to the scarce literature comparing the economic cost of exposure to a pollutant across all of the commonly used methodologies. Further, this is the first study to use primary data to apply non-market valuation methods to estimate the individual willingness to pay for a reduction in symptom days and perceived pollution levels from exposure to wildfire smoke. Wildfires will continue to occur and decisions about the appropriate amount of resources to put towards fire management will likely remain an important debate. The economic cost of human health effects from exposure to wildfire smoke represents one economic impact of wildfires where data and research fall short. We present methods and applications to monetize this value and hope this provides an important contribution to the literature.

SURVEY INSTRUMENT

COVER LETTER

Department of Agricultural and
Resource Economics

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(970) 491-6325
FAX: (970) 491-2067
http://dare.agsci.colostate.edu

Name
Street Address
City State, Zip Code

Dear Name:

As the largest fire in Los Angeles County's history, the recent *Station Fire* affected the residents of Southern California in many ways. Homes were destroyed, some residents evacuated their homes, and smoke filled the air. We know that the experience of having a wildfire occur near your home can be extremely stressful.

While fires such as this one can have many different effects, something that is often overlooked is the health effects that result from the smoke and ash.

We are conducting the enclosed survey in an effort to assess your household's experience with wildfire smoke and ash from the *Station Fire*. We would like to know about any effects it has had on your health and the health of other members of your household. We would also like to know about any preventative actions you may have taken in response to the smoke and ash**. It is important to hear from each and every person who lives in your area, whether you were affected or not.**

The information you provide will be given to wildfire management agencies to help them decide on the best way to manage future wildfires in an effort to minimize the health effects from wildfire smoke and ash.

You are one of a small number of households being asked about the effects of the *Station Fire* on you and your family's health. In order for the results of this study to truly represent the effects on Southern California residents such as yourself, it is important that each questionnaire be completed and returned. The survey booklet contains all of the information you need to complete the survey. There are no right or wrong answers!

A stamped return envelope has been provided to make it easy to mail your survey back to us.
Your responses are confidential and you will not be individually identified in our results.

If you have any questions, please call me at 970-491-2485 or email me at: John.Loomis@colostate.edu. I will be happy to answer any questions you have. We look forward to receiving your survey in the days ahead.

Sincerely,

Dr. John Loomis, Professor

Your Health During the Station Fire

Tell Us What You Think

Colorado State University

Section A: Experience During the *Station Fire*

Smoke and ash from the *Station Fire* caused air-quality problems during the period from Wednesday, August 26 until Wednesday, September 9. While the costs of fire-fighting are easy to calculate, the effect on you and your household's health are not known. Therefore, the purpose of this survey is to learn about possible health effects related to smoke and/or ash during the time of the fire. You and your household may or may not have had any health problems, or you may have taken preventative actions to reduce the chance that you would have problems. Understanding the various ways smoke and ash affected your household is important to help policy-makers assess the overall impact of the fire.

Your responses are completely confidential. Please answer questions to the best of your ability.

1. During the time period Wednesday, August 26 until Wednesday, September 9 were you at the address where this survey was sent? (*Check one box)*

☐ Yes, all of the time

☐ Yes, I was at the address where this survey was sent some of the time

→ How many days? __________

☐ No → Thank you for your time, there is no need to complete the rest of the survey.
Please return the survey in the postage paid envelope.

2. Could you smell smoke and/or ash **outside your home** during the fire and the weeks following? *(Check one box)*

☐ Yes → How many days did you notice the smell? *(Check one box)*

☐ 1-5 days ☐ 6-10 days ☐ 11-15 days ☐ more than 15 days

☐ No

3. Could you smell smoke and/or ash **inside your home** during the fire and the weeks following? *(Check one box)*

☐ Yes → How many days did you notice the smell? *(Check one box)*

☐ 1-5 days ☐ 6-10 days ☐ 11-15 days ☐ more than 15 days

☐ No

4. In the table below, we list some actions you might have taken to reduce the possibility of health effects from exposure to the smoke and/or ash from the *Station Fire.* For each action taken, please check the box for the length of time you took the action and fill in the box with the cost of taking the action. If you did not take the action, please check the box "never."

Possible Actions	Never	1-5 days	6-10 days	11 or more days	Cost of Action
Evacuated / left area affected by smoke					$
Covered face with a mask (dust, surgical, etc.)					$
Used an air filter, air cleaner, or humidifier					$
Avoided going to work					$__________of lost income
Removed ashes from property (yard, car, pool, etc.)					$
Ran air conditioner more than usual					
Stayed indoors more than usual					
Avoided normal outdoor recreation activities/exercise					

5. Overall, how effective do you think the actions you identified in Question #4 were at reducing or eliminating the health effects from exposure to the wildfire smoke and/or ash? *(Check one box)*

☐ Very effective ☐ Not at all effective

☐ Somewhat effective ☐ Don't know

☐ A little effective ☐ Not applicable

6. During the *Station Fire*, did you hear or read about the health effects of wildfire smoke and/or ash from any news articles, public service announcements, or local air quality reports? *(Check one box)*

☐ Yes → Did you change your normal routine based on this information? *(Check one box)*

☐ Yes ☐ No

☐ No

7. Do you think exposure to the smoke and/or ash from the *Station Fire* could affect a person's health? *(Check one box)*

☐ Yes

☐ No

☐ Don't know

Section B: Specific Health Effects During the *Station Fire*

In this section we focus on how exposure to the smoke and/or ash from the *Station Fire* affected your health and the health of up to three other members of your household. Members of your household include all people living in your home who share possessions, money, and make major decisions together (including children). Throughout the rest of the survey when you see the term "up to three members of your household" please respond with the same people in mind.

1. During the *Station Fire* did you or any other members of your household experience symptoms or health effects from exposure to the smoke and/or ash? These include ear, nose and throat symptoms, breathing problems, heart problems and any other symptom due to exposure to the smoke and/or ash. *(Check one box)*

   ☐ Yes → How many? _______________ number of household members with symptoms or health effects

   ☐ No → Please go to Section C

2. What are the ages of up to three members of your household plus yourself who experienced symptoms or health effects from exposure to the smoke and/or ash from the wildfire? *(Fill in the blanks)*

   __________ **your** age

   __________ age of **person 1**

   __________ age of **person 2**

   __________ age of **person 3**

Please respond to the rest of the questions in this section such that **person 1** is the same person whose age you reported for **person 1** in Question #2 above. Likewise for **persons 2 and 3**.

3. For each symptom or health effect listed below, please check the appropriate box if you and/or up to three members of your household experienced it during the *Station Fire*.

	You	**Person 1**	**Person 2**	**Person 3**
Ear, nose and throat symptoms (cough, sore throat, burning eyes, runny nose, sinus problems, etc.)	☐	☐	☐	☐
Breathing problems (shortness of breath, aggravation of asthma, bronchitis, emphysema, etc.)	☐	☐	☐	☐
Heart problems (rapid heartbeat, chest pain, etc.)	☐	☐	☐	☐
Other symptoms related to exposure to smoke and/or ash (anxiety, nausea, dizziness, etc.)	☐	☐	☐	☐

4. What was the total number of days that you and/or up to three members of your household experienced at least one of the symptoms or health effects listed in Question #3 from exposure to the smoke and/or ash? (*Fill in the blanks)*

    __________ total number of days **you** experienced symptoms or health effects

    __________ total number of days **person 1** experienced symptoms or health effects

    __________ total number of days **person 2** experienced symptoms or health effects

    __________ total number of days **person 3** experienced symptoms or health effects

5. On a scale of 1-5, how would you rate the overall level of pain or discomfort from the symptoms or health effects listed in Question #3? *(Circle one number for each household member that had symptoms)*

	No pain or discomfort				Severe pain or discomfort
You	1	2	3	4	5
Person 1	1	2	3	4	5
Person 2	1	2	3	4	5
Person 3	1	2	3	4	5

6. Now we are interested in medical care that may have been received for the breathing problems or heart problems you and/or up to three members of your household suffered. If none of you suffered either of these health effects, please go to Question #8.

Please check all medical visits taken by you and/or up to three members of your household. Please **only** include medical visits made as a result of symptoms or health effects from exposure to the wildfire smoke and/or ash:

	You	**Person 1**	**Person 2**	**Person 3**
Physician visit due to:				
Breathing Problems	☐	☐	☐	☐
Heart Problems	☐	☐	☐	☐
Urgent care visit due to:				
Breathing Problems	☐	☐	☐	☐
Heart Problems	☐	☐	☐	☐
Emergency room visit due to:				
Breathing Problems	☐	☐	☐	☐
Heart Problems	☐	☐	☐	☐
Admitted to hospital due to:				
Breathing Problems	☐	☐	☐	☐
Heart Problems	☐	☐	☐	☐

7. How much time did you and/or up to three members of your household spend traveling to, waiting for and receiving medical care for symptoms or health effects related to exposure to smoke and/or ash from the *Station Fire?* (*Fill in the blanks)*

    __________ total number of hours **you** spent traveling, waiting for and receiving medical care

    __________ total number of hours **person 1** spent traveling, waiting for and receiving medical care

    __________ total number of hours **person 2** spent traveling, waiting for and receiving medical care

    __________ total number of hours **person 3** spent traveling, waiting for and receiving medical care

8. How much money did you and/or up to three members of your household spend on the following items due to symptoms or health effects related to exposure to smoke and/or ash from the *Station Fire? (Please enter the dollar amount. If you spent nothing on an item, please enter $0)*

	You	**Person 1**	**Person 2**	**Person 3**
Medical visits and prescribed medicines	$_______	$_______	$_______	$_______
Non-prescription medicines (e.g. antihistamines, eye or cough drops, etc.)	$_______	$_______	$_______	$_______
Visits to a non-traditional health provider (e.g. chiropractor, herbalist, acupuncturist, etc.)	$_______	$_______	$_______	$_______

9. How many days of work did you and/or up to three members of your household lose as a result of the symptoms or health effects from exposure to the smoke and/or ash from the *Station Fire*? *(Fill in the blanks)*

    __________ total number of days of work **you** missed

    __________ total number of days of work **person 1** missed

    __________ total number of days of work **person 2** missed

    __________ total number of days of work **person 3** missed

10. How many days of recreational activities did you and/or up to three members of your household lose as a result of symptoms or health effects from exposure to the smoke and/or ash from the *Station Fire*? *(Fill in the blanks)*

    __________ total number of days of recreation **you** missed

    __________ total number of days of recreation **person 1** missed

    __________ total number of days of recreation **person 2** missed

    __________ total number of days of recreation **person 3** missed

Section C: Reducing the Effects of Wildfire Smoke and Ash on You & Your Family

Next we are going to ask you a question about what it would have been worth to you to reduce some of the effects your household may have experienced due to exposure to the smoke and/or ash from the *Station Fire*. The *Station Fire* damaged and destroyed homes, resulted in the evacuation of families and pets, and the smoke and ash affected the health of some people. When responding to the question below, **please consider:**

1) **The health effects experienced from the smoke and/or ash.**
2) **Preventative actions you took to avoid health effects from the smoke and/or ash.**
3) **Lost work you or your household experienced to deal with the smoke and/or ash.**
4) **Lost recreation you or your household experienced to deal with the smoke and/or ash.**

Do *not* consider what it would have been worth to you to avoid some of the other effects of the *Station Fire* (such as damage to your home, etc.)

1. Did you or **any other** members of your household experience any of the effects listed in numbers 1-4 above?

   ☐ Yes

   ☐ No → Please go to Section D

2. Knowing what you now know about the *Station Fire*, would you have *paid* $___________ one time to reduce in **half** *the number of days of health effects, days of preventative actions* you took to avoid health effects, and *days of lost work or recreation* you and/or other members of your household experienced during the *Station Fire*? *(Check one box)*

   ☐ Yes

   ☐ No

3. Please tell us how certain you are that you would actually pay (if you said yes) or not pay (if you said no) the stated amount in Question #2 on a scale of 1-10, where 1 means "very uncertain" and 10 means "very certain."

1	2	3	4	5	6	7	8	9	10
very uncertain									**very certain**

4. Please tell us why you answered **Question #2** the way you did.

____

____

____

Section D: Your Health History

In this section, we ask about your general health. As with the rest of the information in this survey, all responses are completely confidential.

1. On average, how many **times per week** do you exercise (include any form of exercise such walking, biking, yoga, etc.)? *(Check one box)*

☐ 0 times per week → Please go to Question #3

☐ 1-2 times per week

☐ 3-5 times per week

☐ More than 5 times per week

2. On average, how many **hours per week** do you spend in indoor and outdoor recreation activities/exercise (including walking, bike-riding, etc.)? (*Fill in the blank)*

__________ hours per week of **indoor** recreation

__________ hours per week of **outdoor** recreation

3. Have you smoked at least 100 cigarettes in your entire life? *(Check one box)*

☐ Yes → Are you currently a smoker? *(Check one box)*

☐ Yes ☐ No

☐ No

4. On average, how many alcoholic drinks do you have per week? *(Check one box)*

☐ None

☐ 1-7

☐ 8-14

☐ More than 14

5. How would you rate your overall health? *(Check one box)*

☐ Excellent

☐ Good

☐ Fair

☐ Poor

6. Do you visit a physician once every year or two for general check-ups? *(Check one box)*

☐ Yes

☐ No

7. Has a physician ever diagnosed you with a chronic respiratory disease (e.g. asthma, respiratory allergies, emphysema, chronic bronchitis, chronic obstructive pulmonary disease, etc.)? *(Check one box)*

☐ Yes → Was it still present in the last 12 months? *(Check one box)*

☐ Yes ☐ No

☐ No

8. Has a physician ever diagnosed you with a heart disease (e.g., coronary artery disease, congestive heart failure, ischemic heart disease, etc.)? *(Check one box)*

☐ Yes → Was it still present in the last 12 months? *(Check one box)*

☐ Yes ☐ No

☐ No

9. Before the *Station Fire*, have you ever noticed a temporary increase in health problems as a result of exposure to smoke and/or ash from a wildfire? *(Check one box)*

☐ Yes

☐ No

Section E: Please Tell Us About Yourself

In this section we ask about your background. As with the rest of the information in this survey, all responses are completely confidential.

1. Are you *(Check one box)*

☐ Male

☐ Female

2. Are you married? *(Check one box)*

☐ Yes

☐ No

3. In what year were you born? *(Fill in the blank)* 19__________

4. What was the zip code where you lived between August 26, 2009 and September 9, 2009? *(Fill in the blank)*

_________ zip code

5. How long have you lived in this zip code? *(Fill in the blank)* __________ years __________ months

6. Do you have health insurance? *(Check one box)*

☐ Yes

☐ No

7. Which category best describes your racial or ethnic identification? *(Check all that apply)*

☐ Black
☐ White
☐ Hispanic/Latino
☐ American Indian or Alaska Native
☐ Asian
☐ Other
☐ Native Hawaiian/Other Pacific Islander

8. What is your highest level of education? *(Check one box)*

☐ Eighth Grade or Less
☐ Some High School
☐ High School Graduate
☐ Some College or Technical School
☐ College or Technical School Graduate
☐ Some Graduate School
☐ Advanced Degree (M.D., M.A., Ph.D., etc.)

9. How many total members are in your household? *(Fill in the blanks)*

__________ number of people in your household under 18 years of age

__________ number of people in your household 18 to 60 years of age

__________ number of people in your household over 60 years of age

10. Which of the following best describes your current employment situation? *(Check one box)*

☐ Employed full-time

☐ Employed part-time

☐ Not employed → Please go to Question #12

☐ Retired → Please go to Question #12

11. Are you paid hourly or are you on salary? *(Check one box)*

☐ Hourly → What is your hourly wage (before taxes)? $__________

→ How many hours per month do you typically work? __________ hours

☐ Salary → What is your current monthly salary (before taxes)? $__________

12. How many members of your household contribute to paying the household expenses? *(Fill in the blank)*

__________ number of household members who help pay household expenses

13. Including these people, what was your approximate household income from all sources in 2008 (before taxes)? *(Check one box)*

☐ less than $19,999	☐ $50,000-$59,999	☐ $90,000-$99,999
☐ $20,000-$29,999	☐ $60,000-$69,999	☐ $100,000-$149,999
☐ $30,000-$39,999	☐ $70,000-$79,999	☐ $150,000-$199,999
☐ $40,000-$49,999	☐ $80,000-$89,999	☐ More than $200,000

14. Was your home damaged or destroyed as a result of the *Station Fire*? *(Check one box)*

☐ Yes, damaged

☐ Yes, destroyed

☐ Neither

Comments

Thank you for completing the survey!

If you have any additional comments please feel free to write them in the space below. When you are finished, please place the survey in the postage paid return envelope and mail it back to us.

If the return envelope was misplaced, please send the completed survey to:

Professor John Loomis
Department of Agricultural and Resource Economics
Clark B-320
Colorado State University
Fort Collins, CO 80523-1172

REMINDER POSTCARD

Department of Agricultural and
Resource Economics

Fort Collins, Colorado 80523-1172
(970) 491-6325
FAX: (970) 491-2067
http://dare.agsci.colostate.edu

Last week a questionnaire asking about your household's experience with the smoke and ash from the *Station Fire* was mailed to you.

If you have already completed and returned the questionnaire, please accept our sincere thanks. If you have not, please complete the survey and mail it back to us in the postage paid return envelope.

Because this questionnaire has been sent to only a small, but representative sample of Los Angeles County residents, your responses will be very useful to wildfire management agencies.

If your questionnaire has been misplaced, please call me at (970) 491-7307 or email me at John.Loomis@colostate.edu and I will mail you one today.

Sincerely,

Dr. John Loomis
Colorado State University