Journal of Forest Economics 18 (2012) 14–35

Contents lists available at ScienceDirect

Journal of Forest Economics

journal homepage: www.elsevier.de/jfe

The hidden cost of wildfires: Economic valuation of health effects of wildfire smoke exposure in Southern California

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ARTICLE INFO

Article history:
Received 23 December 2010
Accepted 6 May 2011

Keywords:
C31
C36
I12
Q51
Q53

Keywords:
Wildfire
Health effects
Defensive behavior method
Willingness to pay
Cost of illness
Station Fire

ABSTRACT

There is a growing concern that human health impacts from exposure to wildfire smoke are ignored in estimates of monetized damages from wildfires. Current research highlights the need for better data collection and analysis of these impacts. Using unique primary data, this paper quantifies the economic cost of health effects from the largest wildfire in Los Angeles County's modern history. A cost of illness estimate is $9.50 per exposed person per day. However, theory and empirical research consistently find that this measure largely underestimates the true economic cost of health effects from exposure to a pollutant in that it ignores the cost of defensive actions taken as well as disutility. For the first time, the defensive behavior method is applied to calculate the willingness to pay for a reduction in one wildfire smoke induced symptom day, which is estimated to be $84.42 per exposed person per day.

Published by Elsevier GmbH on behalf of Department of Forest Economics, SLU Umeå, Sweden.

Introduction

As wildfire seasons increase in intensity and length in many parts of the world, 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, 2011). Increased levels of

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1104-6899/$ – see front matter. Published by Elsevier GmbH on behalf of Department of Forest Economics, SLU Umeå, Sweden.
doi:10.1016/j.jfe.2011.05.002

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 relevant tradeoffs 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. In a USDA Forest Service technical report, Gorte and Gorte (1979) explained that in a USDA Forest Service technical report explained that economic justification of fire management expenditures has been called for since the 1920s. 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 the complete economic impacts. 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 in a benefit cost analysis of such programs could result in underinvestment in prevention measures such as prescribed burns or forest thinning.

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 this cost for a sample of individuals exposed to wildfire smoke from California’s Station Fire of 2009.

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

In the following section, the methods that can be adapted to calculate the economic cost of human health damages from exposure to wildfire smoke are presented. The specific application of these methods to California's Station Fire of 2009 is then outlined, 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. Finally, an econometric approach to the analysis is presented, followed by a discussion of results, limitations, and implications of the analysis.

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 estimate 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 estimates 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 estimate.

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 the recommendations made in 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 damage. 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. The COI and damage function approaches ignore these last two components. Agencies such as the U.S. Environmental Protection Agency recognize the inadequacies of using a cost of illness or damage function approach but explain that "Even now, many important morbidity effects are poorly studied from the willingness to pay perspective. . .. Consequently, benefit estimates based on a damage function approach continue to be used in many applications by EPA" (U.S. EPA, NCEE).

Only a handful of studies that estimate the economic cost of health effects from wildfire smoke 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 da Motta et al. (2000a,b). Finally, Hon (1999) and Ruitenbeek (1999) studies adjusted COI 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. One common approach which can be used to calculate this WTP value is 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.[2]

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 is 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. The defensive behavior method and the theoretical framework underlying it are explained in great detail in Dickie (2003) and Freeman (2003). Here we

[2] Other economic valuation techniques which can be used include stated preference approaches such as the contingent valuation method, choice experiments, and conjoint analysis. This paper focused on the revealed preference approach of the defensive behavior method for a number of reasons. First, information about market goods substituted for exposure to pollution, along with their prices, are readily available. Second, past studies have found that individuals do take defensive actions when exposed to wildfire smoke and we wanted to utilize this information. Third, a goal of this paper is to compare WTP values with COI estimates, which are based on a revealed preference approach. Finally, revealed preference approaches avoid issues such as hypothetical and strategic bias that can result from using stated preference methods.

present a simple one period framework to set the stage for our empirical analysis. An individual produces some negative health output according to a health production function (also referred to as a symptom production function) as follows:

$$S = S(P, A, M, S) \tag{1}$$

This health output S, which we specify as the number of days spent sick, 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 in order to reduce or avoid the 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 days are 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):

$$-p_A\left[\frac{\partial S/\partial P}{\partial S/\partial A}\right] \tag{2a}$$

or

$$-p_M\left[\frac{\partial S/\partial P}{\partial S/\partial M}\right] \tag{2b}$$

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:

$$\frac{-p_A}{\partial S/\partial A} \tag{3a}$$

or

$$\frac{-p_M}{\partial S/\partial M} \tag{3b}$$

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.

The Station Fire

Study area

As the largest wildfire in Los Angeles County's modern history and the 10th largest in California, the Station Fire of 2009 impacted the lives of thousands of people. The fire began on August 26, 2009 in the Angeles National Forest, adjacent to the Los Angeles County metropolitan area, and over time proved increasingly 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 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

Fig. 1. Station Fire location.

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. Fig. 1 shows that location of the Station Fire within the United States.

Data collection

To implement the defensive behavior method, a survey was created in the summer of 2009 and focus groups were held in Anaheim, California the same summer to pretest the survey. Approximately six weeks after the Station Fire began the survey was mailed to a random sample of residents in five cities in the vicinity of the Station Fire. The five cities surveyed 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 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. It should be noted that many other cities in Southern California not included in the sample for this study were also issued smoke advisories. While the cities we surveyed were not randomly drawn from the full population of cities exposed to wildfire smoke during the 2009 Station Fire, we expect that the residents in these five communities are likely representative of residents in other smoke affected communities. We do not attempt to extrapolate our results to the entire population exposed to wildfire smoke during the 2009 Station Fire.

The first survey mailing took place about six weeks after the wildfire began. At this time, the wildfire was 99% contained and respondents had enough time to return home and check their mail if they had evacuated due to the fire. This helped ensure that even those individuals who left their homes to avoid the worst health effects from exposure to the wildfire smoke were still included in the sample. During focus groups, participants indicated that waiting too long to mail the survey may make it difficult for respondents to accurately recall all of the necessary information needed to implement the defensive behavior method. Two follow-up survey mailings were implemented to non-respondents well after the fire was fully contained and reminder postcards were sent between each mailing. The three survey mailings took place over a two month period.

An important aspect of applying the defensive behavior method is to capture all individuals exposed to the pollutant at hand, whether or not they experienced health effects from this exposure. In order to avoid receiving responses from only those individuals who experienced health effects from this exposure, a cover letter preceded the survey in all three mailings. In the first mailing, the cover letter stressed in bold letters that it was important to hear from every person in the area whether they were affected by the wildfire smoke or not. In the second mailing cover letter this statement was expanded, again in bold letters, to stress to the respondent that they were one of a small number of households being surveyed and it was important that they fill out the survey even if their household experienced no health effects at all. Finally, in the third mailing cover letter, again in bold letters, the respondent was reminded that even if their household experienced no health effects at all from the wildfire smoke, we would like to know how they avoided these health effects and they would only need to fill out a portion of the survey. The wording on these cover letters was carefully chosen in an effort to encourage the full sample of individuals to respond, even if they did not experience health effects from exposure to the wildfire smoke.

Survey respondents who were not at home from the first day the wildfire began through the two weeks following this start date were asked to return but not complete the survey. It is highly unlikely that this would have excluded individuals who evacuated due to the fact that the first night the Station Fire burned it was reported as having low growth potential and no potential future threat. The projected final size of the wildfire was only 15 acres as it was estimated to be contained at 1 pm the next day. It was not until a few days later that the wildfire became difficult to contain due to unfavorable weather and terrain. As a result, the survey respondents who were not home during this period were likely not home for reasons unrelated to the wildfire. If respondents left their home on any day after the first day the fire began, they were asked to complete the whole survey. In this way, individuals who evacuated could still be captured. The initial sample size for this study was 1000 individuals obtained from Survey Sampling International, 40 surveys were not deliverable, and 458 complete surveys were returned for an overall response rate of 48%. After removing incomplete surveys and surveys from respondents who were not home during the fire period, there remained a total of 413 usable surveys.

To gather data for the defensive behavior method, the survey questioned respondents about the health effects they experienced during the wildfire, the time spent on averting and mitigating actions, along with the costs of these actions where appropriate, the respondents health history, lifestyle factors, and demographic information. Various averting and mitigating activities were presented to respondents, and they could indicate whether or not they undertook each one. Before presenting respondents with these actions, they were told to specify only those actions taken to reduce the possibility of health effects from exposure to the smoke from the Station Fire and not for any other reason. This ensures that the marginal effect of the use of these actions on symptom days is accurately calculated. Averting activities were chosen based on recommendations from the Centers for Disease Control and Prevention and the U.S. Environmental Protection Agency on what to do during a fire to decrease exposure to the smoke, as well as what previous studies have found in regards to the actions people do in fact take during wildfires (Mott et al., 2002; Kunzli et al., 2006). A description of all study variables and their summary statistics can be found in Table 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 10 μm in diameter and smaller because these can easily enter the lungs and cause serious health impacts. Wildfire smoke contains particles which are 2.5 μm in diameter and smaller, referred to as PM 2.5, as well as particles which are 10 μm in diameter and smaller, referred to as PM 10 (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).

During the Station Fire of 2009, daily average levels of PM 2.5 reached as high as 82.9 $\mu g/m^3$ in Glendora and 38 $\mu g/m^3$ in Burbank, and exceeded 24-h average federal 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 1 h concentrations of PM 2.5 were as high as 223 $\mu g/m^3$ in Glendora and 189 $\mu g/m^3$ in Burbank. Air quality data for PM 10 is available for the city of Glendora only, where daily average concentrations reached

Table 1
Variable definitions and summary statistics.

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
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
Objective pollution levels					
Average daily maximum CO concentration	Parts per million (ppm)	1.47	0.11	1.4	1.8
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
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
Used a 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
Mitigating actions					
Obtained medical care/prescription medications	1 = yes, 0 = no	0.06	0.24	0	1
Took non-prescription medications	1 = yes, 0 = no	0.13	0.33	0	1
Went to a 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 days of recreation activities	1 = yes, 0 = no	0.28	0.45	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

Table 1 (*Continued*)

Variable	Coding	Mean	Std. dev.	Min	Max
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
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/technical school 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
Unemployed	1 = yes, 0 = no	0.08	0.27	0	1
Retired	1 = yes, 0 = no	0.35	0.48	0	1
Has health insurance	1 = yes, 0 = 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
Number of household members with symptoms	Continuous	0.90	1.27	0	6
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

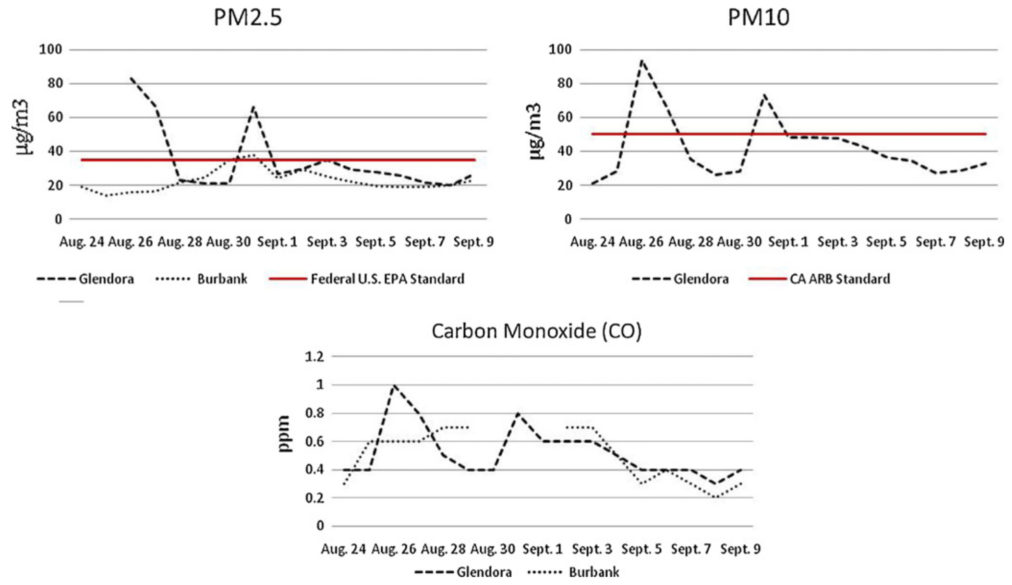

Fig. 2. Daily average concentrations of PM 2.5, PM 10 and CO – August 24–September 9, 2009.

93.8 μg/m^3 and exceeded 24-h state standards for three days. One hour peak concentrations reached 214.4 μg/m^3 in Glendora. National standards for carbon monoxide were not exceeded. 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-h mean PM 2.5 concentration of 63.1 μg/m^3 during two spike days following the wildfire. For the same wildfire, Vedal and Dutton (2006) reported 24-h mean concentrations of PM 2.5 of 44–48 μg/m^3 and peak 1 h concentrations of 200 μg/m^3. Wu et al. (2006) estimated PM 2.5 concentrations of 75–90 μg/m^3 during the 2003 Southern California wildfires.

Fig. 2 shows daily average levels of PM 2.5 and CO in the cities of Glendora and Burbank and daily average levels of PM 10 in Glendora during the two weeks following the start of the Station Fire. These graphs also illustrate the 24-h average federal U.S. EPA standard for PM 2.5 and the separate California Air Resources Board standard for PM 10. 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.

Respondent sample statistics

Given that there is air quality monitoring data for the cities of Glendora and Burbank only, along with recent findings that subjective, within-community pollution measures can be quite different from objective, community-wide measures (Kunzli et al., 2006), the survey questioned respondents about the smoke they smelled indoors and outdoors during the weeks following the start of the Station Fire. Of the 413 survey respondents, 90% reported that they believe that wildfire smoke can affect a person's health and 38% experienced at least one health symptom from exposure to the wildfire smoke. Table 2 summarizes the number and percentage of all survey respondents who experienced each type of symptom, as well as the number and percentage of respondents experiencing each type of symptom based on the number of days smoke from the wildfire was smelled both inside and outside the home. For instance, of the 175 individuals who did not smell smoke indoors, 36 of them (21%) experienced at least one symptom. A clear pattern emerges showing that as the number of days that smoke was smelled either inside or outside the home increases, so does the percentage of respondents experiencing each type of health symptom. Since 42% of individuals did not smell wildfire smoke inside

Table 2
Health effects experienced from Station Fire smoke.

	At least one symptom	Ear, nose or throat symptoms	Breathing symptoms	Heart symptoms	Other symptoms
All Respondents (n = 413)	156 (38%)	147 (36%)	76 (18%)	18 (4%)	36 (9%)
Respondents that:					
Did not smell smoke indoors (n = 175)	36 (21%)	36 (21%)	11 (6%)	2 (1%)	3 (2%)
Smelled smoke indoors for 1–5 days (n = 138)	50 (36%)	48 (35%)	28 (20%)	7 (5%)	13 (9%)
Smelled smoke indoors for 6–10 days (n = 66)	43 (65%)	41 (62%)	25 (38%)	5 (8%)	11 (17%)
Smelled smoke indoors for 11–15 days (n = 23)	16 (70%)	15 (65%)	9 (39%)	2 (9%)	6 (26%)
Smelled smoke indoors for >15 days (n = 11)	8 (73%)	7 (64%)	3 (27%)	2 (18%)	3 (27%)
Did not smell smoke outdoors (n = 22)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Smelled smoke outdoors for 1–5 days (n = 137)	26 (19%)	26 (19%)	10 (7%)	2 (1%)	4 (3%)
Smelled smoke outdoors for 6–10 days (n = 133)	53 (40%)	48 (36%)	25 (19%)	7 (5%)	12 (9%)
Smelled smoke outdoors for 11–15 days (n = 67)	37 (55%)	35 (52%)	19 (28%)	3 (4%)	7 (10%)
Smelled smoke outdoors for >15 days (n = 54)	40 (74%)	38 (70%)	22 (41%)	6 (11%)	13 (24%)

their home and 62% did not experience any health effects at all from exposure to the wildfire smoke, it appears that the survey captured a good mix of those individuals who were heavily affected by the smoke as well as those individuals who were less exposed or less affected.

The defensive behavior method is based on the assumption that individuals take averting and mitigating actions when exposed to an environmental contaminant such as wildfire smoke, making it important to ensure that a good portion of respondents actually engaged in these actions before applying the method (Dickie, 2003). We find that 89% of respondents in our sample took at least one averting action and 16% took at least one mitigating action to minimize the effects of the smoke during the weeks following the start of the fire. Table 3 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 recoded to the highest value without the outlier. Table 3 with these outliers not recoded can be found in Appendix A, Table A.1. Medical costs reported in Table 3 reflect private, out of pocket costs of medical treatment paid by the patient, rather than total costs also incurred by insurance providers and the medical provider.

Finally, to identify how representative the sample of respondents is to the population of residents in the five surveyed cities, Table 4 shows this comparison for a number of demographics. Data for population characteristics were taken from the U.S. Census Bureau's 2005–2009 American Community Survey five-year estimates and averaged across the five cities. Where data on the population mean was available, a one-sample mean comparison t test is conducted to test the equality of means between the sample distribution and the population value. The null hypothesis that the sample has the same mean as the population can be rejected at the 5% level for all variables except unemployment status. Thus, the sample of survey respondents represents a group that is more heavily male, married, white, and educated but less employed, compared to the population of these five cities. The sample of survey respondents likely contains a higher percentage of males than the population due to the fact that the survey was sent to the head of household, which is more frequently listed as the male in the household.

Table 3
Averting and mitigating actions taken by respondents and average expenditure on each ($N = 413$).

	Number of survey respondents	Percentage of survey respondents	Average expenditure
Averting actions			
Evacuated	23	5.6%	$257.95
Wore a face mask	29	7.0%	$6.04
Used a home air cleaner	88	21.3%	$26.93
Avoided going to work	19	4.6%	$219.41[a]
Removed ashes from property	237	57.4%	$8.67
Ran air conditioner more than usual	249	60.3%	$27.66[b]
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[c]
Took non-prescription medications	52	12.6%	$16.86
Went to non-traditional healthcare provider	5	1.2%	$33.00
Missed work	15	3.6%	$691.76
Missed days of recreation activities	114	27.6%	NA

[a] Lost earnings reported by respondent.
[b] 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 kW h 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.
[c] 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.

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 Eq. (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

Table 4
Comparison of sample vs. population demographics.

	Sample	Population	Test statistic (p-value)
Male	59.8%	48.2%	4.775 (0.001)
Married	69.0%	50.7%	7.946 (0.001)
White	78.7%	68.5%	5.012 (0.001)
Graduate school graduate	20.0%	13.9%	3.084 (0.002)
College/technical school graduate	61.6%	45.5%	6.693 (0.001)
High school graduate	95.8%	87.7%	8.211 (0.001)
Employed	56.2%	61.3%	2.756 (0.038)
Unemployed	7.7%	6.3%	1.024 (0.307)
Mean Income	$83,517	$90,586	2.579 (0.010)
Median Income	$75,000	$69,071	

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 non-linear framework, we apply a maximum simulated likelihood estimation model developed by Partha Deb and Pravin Trivedi.[3] Following Deb and Trivedi (2006a,b) the model has the following equations for the health outcome and the endogenous binary regressor:

$$Pr[Y_i = y_i|x_i, d_i, l_i] = f(x_i'\beta + \gamma d_i + \lambda l_i) \tag{4}$$

$$Pr[d_i = 1|z_i, l_i] = g(z_i'\alpha + \delta l_i) \tag{5}$$

For our purposes, in the outcome Eq. (4), y_i represents the total number of days symptoms from exposure to 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 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.

In Eq. (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. Eqs. (4) and (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 regressor 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 regressor, conditional on common latent factors, can then be specified as follows:

$$Pr[Y_i = y_i, d_i = 1|x_i, z_i, l_i] = f(x_i'\beta + \gamma d_i + \lambda l_i) * g(z'\alpha + \delta 1_i) \tag{6}$$

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. The estimator maximizes a simulated log likelihood function, which is equivalent to maximizing the log-likelihood function if enough simulation draws are used.

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

Results

To calculate the full economic cost of the health effects from exposure to the smoke from the Station Fire using Eq. (3a) or (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 “Used a 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.[4] As a result, this variable is focused on in the maximum simulated likelihood estimation and used to calculate Eq. (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 5. Expected symptom days were modeled with a negative binomial count data distribution and the endogenous binary regressor, “Used a 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.[5]

Determinants of expected symptom days

The results of the regression model in Table 5 show that the number of days the respondent smelled smoke outside the home has a positive effect on the expected number of symptom days, holding all other variables constant. 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 a home air cleaner has a negative and significant effect on the expected number of symptom days experienced, all else constant. 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 conducted throughout Colorado during the 2002 wildfire season (Henderson et al., 2005). Various demographic factors, including sex, marital status, age, education level, and employment status, were also found to have a significant effect on expected symptom days.

Determinants of home 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 “Used a 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

[4] 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, “Used a 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.”

[5] Results from the full regression model with all potential explanatory variables are available from the author upon request.

Table 5
Treatment-effects negative binomial regression ($N = 377$).

Variable	Coefficient	Robust Std. error	z
Symptom days – negative binomial regression			
Days smoke smelled outdoors	0.106***	0.013	7.940
Ear, nose or throat symptoms	3.507***	0.246	14.250
Breathing symptoms	0.701***	0.182	3.860
Other symptoms	0.642***	0.193	3.320
Male	−0.365**	0.151	−2.420
Married	−0.333**	0.146	−2.280
Age	0.012**	0.005	2.430
College/technical school graduate	0.423***	0.126	3.350
Employed part-time	0.548*	0.306	1.790
Used a home air cleaner	−0.813***	0.162	−5.010
Constant	−3.438***	0.438	−7.850
Used a home air cleaner – probit regression			
Days smoke smelled outdoors	0.039	0.025	1.540
Ear, nose or throat symptoms	0.715***	0.245	2.920
Breathing symptoms	0.180	0.258	0.690
Other symptoms	1.221***	0.335	3.650
Male	−0.181	0.246	−0.740
Married	0.472*	0.271	1.740
Age	−0.005	0.009	−0.530
College/technical school graduate	0.351	0.247	1.420
Employed part-time	0.383	0.454	0.840
Employed full-time	0.469*	0.284	1.660
Income	−0.004*	0.002	−1.660
Believe smoke can affect health	1.323**	0.661	2.000
Constant	−3.287***	1.029	−3.200
λ (latent factor)	0.844***	0.088	9.640
$\ln(\alpha)$	−12.075	29.085	−0.420
N	377		
Log likelihood	−674.637		
Wald chi2 (22)	736.68		
Prob > chi2	0.0000001		

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

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. Various demographic factors, such as marital status and employment status, were also found to have a significant effect on the decision to use a home air cleaner.

A variable controlling for whether the individual heard or read about the possible health effects that could result from exposure to the wildfire smoke, as well as a variable controlling for whether the individual changed their defensive actions as a result of this, were included in the model but not found to be a significant determinant of using a home air cleaner. This could be due to the fact that while smoke advisories tell individuals to stay indoors, avoid unnecessary outdoor activities and run the air conditioner more, they do not specifically tell individuals to use air cleaners to reduce their exposure. In addition, variables controlling for the number of children present in the household as well as the number of people in the household who experienced health symptoms from exposure to the wildfire smoke were included but not found to significantly influence the decision to use a home air cleaner.

Finally, the positive coefficient on the latent factor, lambda, suggests that individuals who are more likely to use a home 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 exposure to wildfire 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 significant and negative effect on expected symptom days as well as 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 calculated to be −0.319, meaning the use of a home air cleaner is expected to reduce symptom days by 0.319.[6] Taking the average 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. Following Eq. (3a) the average respondent's marginal value of a reduction in one symptom day resulting from exposure to wildfire smoke is equal to −\$26.93/−0.319 = \$84.42. 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 morbidity valuation studies with a health status index, Johnson et al. (1997) estimated values ranging from \$36 to \$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.[7]

Including the full sample of respondents, an average of 3.3 symptom days was experienced. For the 38% of respondents who reported experiencing symptoms, an average of 8.7 symptom days was 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 wildfire smoke, as well as the disutility associated with symptoms or lost leisure. Given that hearing or reading about the potential health effects that could result from exposure to the wildfire smoke was not found to significantly influence the decision to use a home air cleaner, there does not seem to be reason to be concerned that sampling cities that were issued smoke advisory warnings would affect this willingness to pay result. Further, while some averting actions may be taken on behalf of all household members, including children, since variables controlling for the number of children in the household and the number of people in the household who experienced symptoms were not found to significantly influence the decision to use a home air cleaner, this can be viewed as an individual willingness to pay value. Finally, the issue of joint production is a major obstacle to implementing the defensive behavior method (see Bartik, 1988; Bresnahan and Dickie, 1994; Dickie, 2003). For instance, if defensive actions enter the individuals' utility function directly and provide a positive source of utility, willingness to pay values may be inflated. However, survey respondents were asked to focus only on actions taken as a direct result of exposure to wildfire smoke and home air cleaners are typically purchased for the specific reason of reducing pollution levels in the home. Therefore, joint production does not seem to be a major concern in this case.

Cost of illness

A simple cost of illness for one symptom day was calculated using a formula from Alberini and Krupnick (2000). We estimate probit regression models for whether the individual obtained medical care or took prescribed medications, whether non-prescription medications were taken, whether a non-traditional healthcare provider was seen, and whether or not work was missed as a direct result of health symptoms resulting from exposure to the wildfire smoke. Results of these full probit models can be found in Appendix A, Table B.1.

[6] 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.

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

Each model is re-estimated retaining only those variables which were found to have a statistically significant effect on undertaking each action. For each action, we take the predicted probability that the action is taken, with independent variables set at their mean and symptom days set at 1, and multiply this by its average in-sample cost. These are the same average costs reported in Table 3 except for work days lost, which is adjusted to represent the lost wages from one work day lost due to illness. These mitigating actions and their costs are restricted to the surveyed individual, as the survey had the respondent break them down by household member.

It should be noted that these costs represent private rather than social costs due to the fact that the respondent was asked to report out of pocket medical expenses only. Summing costs across all actions results in an average cost of illness of $9.50 per exposed person per day. This cost of illness represents an average private (not social) cost for an individual exposed to wildfire smoke.

The willingness to pay estimate of $84.42 per exposed person per day exceeds this in-sample cost of illness estimate by a factor of about nine.[8] 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 to 3.7 for asthma symptoms due to ozone exposure. Alberini and Krupnick (2000) estimated a WTP:COI ratio ranging from 1.61 to 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 30 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. 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 cost of averting activities 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.

Limitations

A limitation to this study and a potential drawback of applying the defensive behavior method to wildfire smoke exposure is the omission of cost of illness and willingness to pay estimates focused on children. Children are often reported as being a sensitive population affected by wildfire smoke and studies such as Kunzli et al. (2006) focus solely on the health impacts of wildfire smoke on children. However, the goal of this study was to estimate the economic cost of the health effects resulting from exposure to wildfire smoke. To estimate a willingness to pay value for reduced symptom days using the defensive behavior method, the marginal effect of the use of defensive actions on symptom days needs to be estimated. Given that these actions are typically taken by adults, this

[8] Using a bootstrap re-sampling technique (see Efron, 1979, 1982; Efron and Tibshirani, 1993), 95% confidence intervals are constructed around a generated distribution of 1000 values for each estimate. The confidence interval of $71–$1064 for the willingness to pay value does not overlap the confidence interval of $4–$13 for the cost of illness estimate.

study focused on the willingness to pay to reduce adult symptom days only. A variable controlling for the number of children present in the household was included in the regression models but not found to have a significant effect on the probability of using a home air cleaner. Future studies could apply stated preference methods such as the contingent valuation method, to question parents about their willingness to pay to reduce their children's health effects resulting from exposure to wildfire smoke.

Another limitation to this study is that the daily cost of illness estimate is restricted to a private rather than social cost. While this private cost of illness estimate is more comparable to the individual willingness to pay value for a reduction in one wildfire induced symptom day than a social cost, future studies may want to calculate a social cost of illness estimate as well. Finally, while aggregating these cost of illness estimates and willingness to pay values would be necessary in a complete wildfire damage assessment, we do not have readily available an estimate of total population person-days of exposure from the Station Fire. An important area of future research would be to capture an aggregate value of the economic cost of the health effects resulting from exposure to wildfire smoke.

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 from 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, 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). It also 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 an average cost of illness estimate of \$9.50 per exposed person per day. 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. Application of the defensive behavior approach reveals that individuals exposed to wildfire smoke during the Station Fire were willing to pay on average \$84.42 to avoid one day of symptoms resulting from this exposure. 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. It should be noted that both of these measures represent private individual estimates and therefore may underestimate the social costs of health damages from wildfire smoke exposure.

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 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 (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 values 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 include all relevant costs of a given wildfire in damage assessments and accurately apply benefit transfer techniques. For instance, when conducting benefit cost analyses of wildfire management and prevention practices, agencies could estimate the elevated particulate matter concentrations that would be avoided due to a particular prevention measure. They could then multiply the willingness to pay value for a reduction in one symptom day from wildfire smoke exposure by the average number of symptom days that would have been experienced and the number of individuals who would have been affected had this elevation in particulate matter concentrations occurred. This would result in an estimate of one benefit of this prevention measure due to avoided human health effects which could be included in a benefit cost analysis.

Appendix A.

Table A.1
Averting and mitigating actions taken by respondents and average expenditure on each with outliers included ($N = 413$).

	Number of Survey Respondents	Percentage of Survey Respondents	Average Expenditure
Averting actions			
Evacuated	23	5.6%	$471.59
Wore a face mask	29	7.0%	$16.04
Used an air cleaner	88	21.3%	$36.19
Avoided going to work	19	4.6%	$390.00
Removed ashes from property	237	57.4%	$18.91
Ran air conditioner more than usual	249	60.3%	$27.66
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
Took non-prescription medications	52	12.6%	$16.86
Went to non-traditional healthcare provider	5	1.2%	$33.00
Missed work	15	3.6%	$691.76
Missed days of recreation activities	114	27.6%	NA

Table B.1
Determinants of mitigating activities (probit).[a],[b]

Variable	Doctor/prescription Meds.		Non-prescription Meds.		Nontr. healthcare provider		Missed work	
	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	−2.010	1.462	1.229	0.929
6–10 days	−0.596	0.575	0.475	0.337	−1.851	1.657	**1.775**[*]	0.972
11–15 days	0.958	0.694	−0.157	0.565	1.214	1.330	1.353	1.231
>15 days	(Empty)		**1.512**[**]	0.592	(Empty)		(Empty)	
Average daily maximum CO concentration	−1.155	2.111	−0.515	1.296	−47.124	45.045	0.946	2.081
Symptom days	**0.136**[***]	0.032	**0.064**[***]	0.017	0.025	0.059	0.041	0.037
Current respiratory condition	**0.798**[*]	0.408	−0.404	0.321	−1.670	1.586	−0.861	0.742
Current heart condition	−0.530	0.854	−0.577	0.512	(Omitted)		1.027	1.003
Experienced health effects from wildfire smoke in past	−0.236	0.448	**0.757**[***]	0.258	**2.731**[**]	1.352	0.684	0.672
Times per week of exercise	0.019	0.234	−0.108	0.148	0.442	0.594	0.585	0.388
Smoker	0.937	0.648	−1.172	0.888			0.498	0.993
Alcoholic drinks per week	−0.120	0.317	0.194	0.170	−0.053	0.733	−0.119	0.435
Current health is excellent	−1.834	1.241	−1.038	0.917			3.671	327.915
Current health is good	−1.828	1.202	−1.039	0.887			3.774	327.915
Current health is fair	−**1.906**[*]	1.149	−0.867	0.869			(Omitted)	
Hours per week of indoor recreation	0.021	0.052	0.020	0.030			−**0.322**[**]	0.164
Hours per week of outdoor recreation	−0.048	0.041	0.018	0.023			0.020	0.055
Has a regular doctor	(Omitted)		0.033	0.376			−0.557	0.695
Male	−**1.452**[***]	0.512	−**0.542**[**]	0.260	−1.536	1.167	−**1.619**[**]	0.655
Married	**1.208**[**]	0.521	−0.081	0.274	1.433	1.186	0.673	0.725
Age	−0.006	0.016	−0.008	0.010	0.007	0.035	−0.010	0.026
White	−0.342	0.464	−0.046	0.304	−0.884	0.904	−**1.120**[*]	0.665
Graduate school graduate	0.174	0.499	−0.172	0.293			0.567	0.542
College graduate	0.183	0.404	0.264	0.265			1.048	0.803
Employed full-time	−0.088	0.526	0.301	0.324	1.188	1.128	1.073	0.739
Employed part-time	0.074	0.733	−0.827	0.617			0.332	1.024
Has health insurance	0.500	0.773	0.537	0.495			−0.039	0.985
Lives in Duarte	−0.264	0.631	−0.415	0.449			(Omitted)	
Lives in Monrovia	0.033	0.476	0.150	0.301			0.191	0.637
Lives in Burbank	0.165	0.483	0.131	0.307			(Omitted)	
Income	−0.006	0.005	0.000	0.003			0.000	0.006
Heard or read about possible health effects	0.356	0.625	−0.340	0.312	−1.077	0.825	0.482	0.852
Believes smoke can affect health	(Omitted)		(Omitted)				(Omitted)	
Constant	1.124	3.477	0.020	2.280	62.401	62.631	−8.732	327.951
N	287		339		359		187	
Log likelihood		−43.666		−94.202		−12.843		−27.330
LR chi2		82.460		91.690		26.980		44.840
Prob > chi2		0.000001		0.000001		0.028900		0.022900

[a] Given the small number of individuals who went to a non-traditional healthcare provider, all independent variables could not be included in this regression model.

[b] A version of the Hausman specification error test is used to test for the endogeneity of 'Symptom days' in each mitigating action model. This test results in a failure to reject the null hypothesis of exogeneity of this variable in each model.

[*] $p < 0.10$.

[**] $p < 0.05$.

[***] $p < 0.01$.

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