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

Leslie Richardson, John B. Loomis, and Patricia A. Champ

ABSTRACT. *Estimating the economic benefits of reduced health damages due to improvements in environmental quality continues to challenge economists. We review welfare measures associated with reduced wildfire smoke exposure, and a unique dataset from California's Station Fire of 2009 allows for a comparison of cost of illness (COI) estimates with willingness to pay (WTP) measures. The WTP for one less symptom day is estimated to be $87 and $95, using the defensive behavior and contingent valuation methods, respectively. These WTP estimates are not statistically different but do differ from a $3 traditional daily COI estimate and $17 comprehensive daily COI estimate.* (JEL Q51, Q53)

I. INTRODUCTION

A variety of environmental contaminants can negatively affect human health. Therefore government agencies, such as the U.S. Environmental Protection Agency (EPA), are tasked with protecting human health by reducing human exposure to contaminants in the air, water, and land. Branches of the EPA such as the National Center for Environmental Economics are responsible for analyzing the economic impacts, in other words, costs and benefits, of environmental regulations and policies. Quantifying these impacts can inform decision making by highlighting the trade-offs involved with policies aimed at improving environmental quality. However, the challenge of accurately monetizing the economic benefits of a reduction in human health damages associated with policies that effectively reduce pollution levels has remained pervasive in the economics literature, as well as the policy realm.

Freeman (2003) explains that improvements in environmental quality can benefit an affected individual by reducing some or all of the following adverse impacts: incurred medical expenses due to treating illness caused by pollution exposure; lost wages from the inability to work; expenditures and activities taken to defend oneself against the possible health effects associated with exposure; and the disutility associated with symptoms or lost leisure caused by illness. The lack of a monetary equivalent to some of these adverse effects complicates monetization of the full benefits of a reduction in pollution concentrations. In addition, an analyst cannot simply add together the monetary equivalent of changes in these components to arrive at the correct welfare measure of the benefits of reduced pollution concentrations or the health effects resulting from them. This is largely due to the fact that medical expenses are an exogenous outcome of illness, whereas defensive activities are chosen optimally by the individual (see Bockstael and McConnell 2007). Rather, there are measures based on these components that can be used to quantify, or approximate, these benefit estimates. Three approaches commonly used to monetize the benefits of improvements in human health associated with reductions in the concentrations of various pollutants are the defensive behavior method (DBM), the contingent valuation method (CVM), and the cost of illness (COI) approach.

Land Economics • February 2013 • 89 (1): 76–100
ISSN 0023-7639; E-ISSN 1543-8325

The authors are, respectively, economist, U.S. Geological Survey, Fort Collins Science Center, Fort Collins, Colorado; professor, Department of Agricultural and Resource Economics, Colorado State University, Fort Collins; and economist, U.S. Forest Service, Rocky Mountain Research Station, Fort Collins, Colorado.

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 DBM and CVM to estimate the willingness to pay (WTP) for a reduction in one wildfire smoke–induced symptom day. To our knowledge, these are the first WTP estimates for a reduction in symptom days associated with wildfire smoke exposure. Second, our data allow for a comparison of estimates across all three common approaches used to monetize the benefits of reduced morbidity. To statistically test for a significant difference in the three estimates, we test for overlapping confidence intervals and, where appropriate, carry out a complete combinatorial test. In addition, the study results shed light on WTP:COI calibration factors for the health damages associated with wildfire smoke specifically.

II. THEORETICAL FRAMEWORK

Defensive Behavior Method

The DBM is a revealed preference approach used in the field of health and environmental economics. The method originates from a health production function first outlined by Grossman (1972), with extensions to the model undertaken by Cropper (1981) and Harrington and Portney (1987). The general idea of the DBM in the health production function framework is that if an individual experiences some negative health output, such as a number of days with symptoms, it enters into his utility function as follows:

$$U = U(X,L,S), \qquad [1]$$

where X represents consumption of a composite market good, L represents leisure time, and S represents symptom days. It can be assumed that utility is increasing in consumption of X and L and decreasing in S. This health output S is not exogenous but rather "produced" by the individual according to a health production function:

$$S = S(P,D,Z), \qquad [2]$$

where P represents exposure to a pollutant and Z represents a set of exogenous factors that can affect symptom days, such as lifestyle and demographic factors, as well as health status prior to exposure. Further, the individual can choose to invest in the production of his health by taking defensive actions, labeled D. These include actions that serve to decrease symptom days by decreasing exposure to a given pollutant. Examples include evacuating a polluted area, staying indoors, using a home air cleaner to reduce indoor pollution levels, or using preventative medications such as a prescribed inhaler. Symptom days are increasing in P and decreasing in D. Following closely the framework in Dickie (2003), the individual is also subject to a full income budget constraint as follows:

$$\bar{I} + w[T - L - S] = X + p_d D + M(S), \qquad [3]$$

where $\bar{I}$ represents nonlabor exogenous income, w represents labor income, and the individual is assumed to allocate his total time available T between work, leisure, and time spent sick. The price of X is normalized to 1, defensive actions have an associated cost of p_d, and the individual may also incur medical costs as a function of the possible illness experienced, represented by $M(S)$. This constraint can be rewritten as

$$\bar{I} + wT = X + wL + p_d D + M(S) + wS. \qquad [4]$$

Therefore, the individual's total budget is spent on the consumption of goods, leisure, defensive actions, medical expenditures, and indirect costs of time lost due to illness. The individual's costs of illness are represented by the last two components of [4]:

$$COI(S) = M(S) + wS. \qquad [5]$$

These costs represent an exogenous outcome of illness. Following Dickie (2003), this utility maximization problem can be solved in stages, where the individual first chooses defensive actions to minimize defensive expenditures ($p_d D$), subject to producing a given amount of symptom days, resulting in the following first-order conditions:

$$p_d - \pi(\partial S(\cdot)/\partial D) = 0,$$
$$S^0 - S(\cdot) = 0, \qquad [6]$$

where S^0 is the given amount of symptom days and π is the Lagrangean multiplier. These first-order conditions can be solved to obtain values of D and π as a function of prices, symptom days, pollution levels, and any other exogenous factors that minimize defensive expenditures while achieving symptom days S^0. These can be used to define the defensive expenditure function (Bartik 1988) as follows:

$$DE(p_d, S^0, P, Z) = p_d D^0. \quad [7]$$

Utilizing first-order conditions and the envelope theorem, which tells us that the marginal cost of symptom days equals the Lagrangian multiplier π, we have

$$(\partial DE/\partial S) = \pi = p_d/(\partial S/\partial D) < 0. \quad [8]$$

In the second stage, the individual chooses the amount of symptom days and consumption of goods and leisure to maximize utility. This can be solved by plugging the defensive expenditure function into the full income budget constraint as follows:

$$\bar{I} + wT = X + wL + DE(p_d, S^0, P, Z) + M(S) + wS. \quad [9]$$

The utility maximization problem becomes

$$\begin{aligned} &\text{Maximize } U = U(X, L, S(P, D, Z)) \\ &\text{s.t. } \bar{I} + wT = X + wL + DE(p_d, S^0, P, Z) + M(S) + wS \end{aligned} \quad [10]$$

The first-order conditions can then be obtained, with the one related to the individual's choice of symptom days being

$$(\partial U/\partial S) - \lambda(\partial DE/\partial S) - \lambda(dM/dS) - \lambda w = 0, \quad [11]$$

which can be rearranged as

$$-(\partial DE/\partial S) = -(\partial U/\partial S)/\lambda + (dM/dS) + w. \quad [12]$$

Finally, to estimate the marginal value of a change in illness dS, which is the focus of this paper, equations [8] and [12] can be used to show that

$$\begin{aligned} -(\partial DE/\partial S)dS &= [-(\partial U/\partial S)/\lambda + (dM/dS) + w]dS \\ &= -[p_d/(\partial S/\partial D)]dS. \end{aligned} \quad [13]$$

By utility maximization, the marginal benefit of reduced time spent sick, that is, the WTP for one less symptom day, must equal the marginal cost of reduced sick time. Since defensive actions are an input to the production of the negative health output, it follows from production theory that the marginal cost of reduced symptom days will equal the ratio of the full price of any of these defensive actions to its marginal product.

Contingent Valuation Method

Unlike the DBM, which looks at the defensive actions individuals take to arrive at a measure of the economic value of a decrease in symptom days, the CVM is a stated preference approach used to estimate this value. In a CVM framework, individuals are asked directly about the value they place on a specific change in a nonmarket good, which in this case would be a decrease in the number of symptom days experienced as a result of exposure to some pollutant. Following the DBM framework, 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:

$$e = e(p_d, P, Z, S^0, u^*). \quad [14]$$

This is the minimum expenditure required to remain at utility level u^* given symptom days S^0, prices p_d, a particular pollution level P, and exogenous characteristics of the individual Z. The WTP for a reduction in symptom days from S^0 to S^1 can be expressed as

$$WTP = e(p_d, P, Z, S^0, u^*) - e(p_d, P, Z, S^1, u^*). \quad [15]$$

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

COI Approach

Given the complexities involved with empirically estimating WTP, agency economists and health professionals frequently rely on a simple COI approach to capture the benefits of changes in morbidity resulting from reduced pollution concentrations. This approach focuses on capturing the direct and indirect resource costs associated with a pollution-induced illness. These costs typically include expenditures on medications and medical care used to treat the illness, the opportunity cost of time spent obtaining medical care, as well as the economic cost of lost wages resulting from time spent sick. The benefits of reduced pollution are measured as the associated reduction in these resource costs (Dickie 2003).

While a COI estimate captures resource costs associated with a pollution-related illness, equation [12] demonstrates theoretically why the COI approach often underestimates the true individual value of a reduction in illness caused by pollution. The marginal benefit the individual receives from reduced time spent sick is the sum of the monetary equivalent of disutility avoided ($-(\partial U/\partial S)/\lambda$), the individual's savings on medical expenditures (dM/dS), and the marginal value of additional time available for work and leisure (w). Monetization of the savings in costs of illness will fail to capture the disutility avoided as a result of improved health. A similar theoretical relationship is derived by Freeman (2003), who explains that for a reduction in illness, marginal WTP is the sum of the COI and the monetary equivalent of the lost utility. However, under very particular circumstances in which exposure to the pollutant does not cause disutility, and the individual cannot take defensive actions to mitigate the negative effects of changes in pollution, the COI will equal the correct welfare measure for a change in pollution concentrations. See Bockstael and McConnell (2007) for the derivation of this case.

The shortcomings of the COI approach in the more general setting where there is disutility of illness are highlighted by the EPA's National Center for Environmental Economics statement that "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" (USEPA 2010b). However, there are various pollutants for which monetized COI estimates remain the only available source of information on the potential benefits of reduced pollution. In these circumstances, policy makers have little choice but to utilize them in damage assessments, whether or not the assumptions necessary for them to represent a correct welfare measure hold. The EPA reports that "many important morbidity effects are poorly studied from the WTP perspective. The COI approach is much more common in valuing chronic illness" (USEPA 2010b).

III. A REVIEW OF THE LITERATURE

The DBM 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, Grossman, and Goldman 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, 1991b), and contaminated water supplies (Harrington, Krupnick, and Spofford 1989; Um, Kwak, and Kim 2002; Dasgupta 2004). In addition, numerous studies have applied the CVM to estimate the WTP to avoid the health damages associated with various pollutants (Rowe and Chestnut 1985; Dickie et al. 1986; Tolley et al. 1986; Dickie et al. 1987; Chestnut et al. 1996; Alberini and Krupnick 2000).

A number of the above studies have looked at the relationship between COI estimates and WTP values for a reduction in health effects from exposure to a pollutant, and the majority of empirical findings support theoretical predictions that costs of illness underestimate WTP. For instance, Rowe and Chestnut (1985) interviewed a panel of asthmatics in Glendora, California, and found that CVM WTP estimates for reductions in the severity of asthma symptoms were 1.6 to 3.7 times the comparable COI estimates. Dickie and Gerking (1991b) interviewed residents in Glendora and Burbank, California, and found that WTP for decreased ozone levels exceeded medical expenses by a factor of 2 to 4. Chestnut et al.

(1996) found that small changes in angina frequency were associated with minor changes in costs of illness but significant changes in WTP. 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 COI estimates, by a factor of 3.1 to 79 times. A more recent study by Chestnut et al. (2006) compared COI and WTP values for preventing hospitalizations resulting from respiratory and cardiovascular illness. The study attempted to monetize a more comprehensive estimate of COI than is commonly used by including nontraditional cost components such as lost household production and lost recreation value due to the hospitalization and recovery period, in addition to medical expenses and lost earnings. They found that comprehensive COI estimates were much larger than previously obtained estimates that excluded nontraditional costs resulting from the hospitalization recovery period. Comprehensive COI estimates actually exceeded WTP values in nearly all cases.

In addition, a handful of studies have examined the relationship between WTP estimates derived from both the DBM and CVM, 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 methods, and compared WTP results across the two. The authors found that WTP estimates derived from the CVM were always larger than their DBM counterparts, by a factor of up to 10 times. However, a year later, Dickie et al. (1987) compiled a new dataset of residents in the same cities. In this survey, respondents were asked their WTP 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 WTP estimates from the CVM were found to be smaller than their DBM counterparts. Dickie et al. (1987) explained that this result is to be expected given that defensive goods used in calculations of WTP from the DBM may provide direct utility to the individual employing them. This should lead to larger benefit estimates than those derived from the CVM. Chestnut et al. (1996) found that CVM WTP estimates to avoid increases in angina were directly comparable to WTP estimates based on defensive expenditures.

As evident from the literature, there is still some uncertainty on the relationship between the estimates produced by the methods commonly used to value a reduction in health effects associated with exposure to a pollutant. Most importantly, while some studies have compared estimates across two of the three approaches used to value decreases in these morbidity effects, aside from Chestnut et al. (1996), none to our knowledge have attempted to compare estimates across all three methods using the same primary data. Such comparisons are needed to assess the validity of the techniques. Further, while the majority of studies compare point estimates of benefit measures, these comparisons can be made even more rigorous and accurate by evaluating statistical tests of their differences. Thus, we statistically test hypotheses about the equality of benefit estimates derived from the DBM, the CVM, and the COI approach.

Wildfire Smoke Exposure

The Centers for Disease Control and Prevention (CDC) and the 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 of being affected by wildfire smoke exposure. Evidence of these morbidity effects has been supported by studies such as those by Duclos, Sanderson, and Lipsett (1990), CDC (1999), Johnston et al. (2002), 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, Huggett, and Holmes 2008; Dale 2009). However, the costs imposed on individuals as a result of these potential health effects are often unknown or underestimated.

While numerous studies have applied a COI approach to calculate the economic cost of health effects from wildfire smoke exposure specifically, to date, none have applied either the DBM or the CVM to calculate the WTP for a reduction in associated health damages. Kochi et al. (2010) conducted a literature review of studies estimating the economic cost of health damages from wildfire smoke exposure, 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.

IV. HYPOTHESIS

In this study, we compare the value of decreased morbidity from wildfire smoke exposure based on estimates from three different valuation methods: the DBM, the CVM, and the COI approach. As explained above, theory and empirical studies demonstrate that the traditional COI approach often underestimates the individual value for a reduction in health effects resulting from exposure to various pollutants. Bockstael and McConnell (2007) do derive a special case in which the COI estimate will equal the correct welfare measure for a change in pollution levels, but note that this is an extreme case. The conditions that need to hold for this equality are that increases in pollution do not cause any disutility, either directly or indirectly through illness, and that the individual cannot take defensive actions to mitigate the effects of changes in pollution concentrations. These conditions are unlikely to be true for wildfire smoke exposure. Past studies have consistently found that 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 (Mott et al. 2002; Kunzli et al. 2006; Kochi et al. 2010). Indeed, during a major wildfire event, smoke advisory warnings are usually issued. These warnings provide specific suggestions for avoiding wildfire smoke. Incorporating nontraditional health costs such as the value of lost nonwork time in COI estimates may help to close the gap between COI estimates and WTP values, as noted by Berger et al. (1987) and Chestnut et al. (2006). In this study we will calculate a traditional COI estimate (COI_{trad}) as well as a comprehensive estimate that incorporates the value of lost recreation days resulting from an illness (COI_{comp}).

The expected relationship between WTP values for reduced morbidity estimated by the DBM and CVM remains unclear from both theoretical results and literature findings. For instance, as noted by Dickie et al. (1987), the defensive goods used in the DBM 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 CVM counterparts. In addition, Carson et al. (1996) conducted a meta-analysis of revealed preference and CVM WTP estimates for quasi-public goods and found that on average, the former are larger than the latter. However, under the DBM, equation [8] shows that the WTP for a marginal reduction in symptom days is equal to the savings in defensive expenditures that just offsets the change in sick days, holding environmental quality constant. However, it is unclear that using actual observed defensive expenditures to estimate this value will hold environmental quality constant, meaning WTP estimated by the DBM could underestimate true WTP (see Courant and Porter [1981], Harrington and Portney [1987], and Bockstael and McConnell [2007], for a derivation of this argument in the context of WTP for changes in environmental quality). Therefore, the hypothesis we test is as follows:

$$H_o\colon\ COI_{\text{trad}} = COI_{\text{comp}} = WTP_{\text{DBM}} = WTP_{\text{CVM}},$$

$$H_a\colon\ COI_{\text{trad}} < COI_{\text{comp}} < WTP_{\text{DBM}} \neq WTP_{\text{CVM}}.$$

While the COI estimates are simply a sample mean, the WTP values will be calculated through more complex mathematical formulas and will not have straightforward properties that facilitate simple 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 used to estimate WTP values. This process will be repeated 1,000 times to generate a distribution of 1,000 values calculated from each of the two WTP methods.[1] 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, for the 90% confidence interval, 5% of the observations at each tail are dropped from the distribution. As explained by Loomis, Creel, and Park (1991), while benefit estimates obtained using different valuation methods may appear to be quite different, comparing confidence intervals is a first step to statistically test for a difference.

If the confidence intervals around two of the values do not overlap, it can be concluded that the null hypothesis for that comparison can be rejected at the specified level of confidence. If the confidence intervals of any two values do overlap at the desired level of confidence, a second approach will be applied. Following Poe, Severance-Lossin, and Welsh (1994) and Poe, Giraud, and Loomis (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 simulated 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 $((WTP_{\mathrm{DBM}})_i - (WTP_{\mathrm{CVM}})_z)$, where $i = 1{,}000$ bootstrapped WTP_{DBM} values and $z = 1{,}000$ bootstrapped WTP_{CVM} values. 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 WTP 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 between the two WTP estimates can be rejected at the 0.05 significance level.

V. SAMPLING FRAME AND DATA

The Station Fire began on Wednesday, August 26, 2009, in the Angeles National Forest, located adjacent to the Los Angeles, California, metropolitan area. It took firefighters 52 days to fully contain the wildfire, which crept into nearby neighborhoods. This became the largest wildfire in Los Angeles County's modern wildfire history and the tenth largest in California's. The smoke from the Station Fire caused nearby residents to experience unhealthy air quality levels, and as a result, smoke advisory warnings were issued by the South Coast Air Quality Management District. These warnings advised residents in any area impacted by smoke to avoid unnecessary outdoor activities, keep windows and doors closed when indoors, and run the air conditioner.

The sample frame for the study was 1,000 randomly selected residents living in five southern California cities (Duarte, Monrovia, Sierra Madre, Burbank, and Glendora) that were exposed to unhealthy air quality levels due to smoke from the Station Fire. A questionnaire was created in the summer of 2009 based on feedback from focus groups held in Anaheim, California, and consultation with health economists. The focus groups allowed participants to pretest and critique the questionnaire based on their experience with the Freeway Complex Fire of 2008.

Approximately six weeks after the Station Fire began, the survey was mailed to the sample of southern California residents. At that time, the wildfire was 99% contained and re-

[1] While other simulation methods including the jackknife, Krinsky and Robb (1986), Cameron (1991), 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.

spondents who had evacuated would have had a chance to return home. Two follow-up mailings were implemented over a two-month period, for a total of three mailings to nonrespondents. Forty 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, there remain a total of 413 usable surveys.

Data on concentrations of particulate matter (PM) and carbon monoxide (CO) 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 with air quality monitoring stations within city limits. However, the other cities 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 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 monitoring 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. Figure 1 provides an approximate location of the cities surveyed and air quality monitoring stations where data were used, in relation to the location of the Station Fire.

Given recent findings by Kunzli et al. (2006) that subjective, within-community pollution measures may reflect wildfire smoke exposure more accurately than objective community-wide measures, the survey questioned respondents about the smoke and/or ash they smelled both inside and outside of their home for the weeks following the start of the fire. If they indicated that they could smell smoke and/or ash, they were asked about the number of days that it was smelled. Table 1 presents both objective and subjective pollution levels by city during the Station Fire. Objective pollution levels are measured by six-day averages of daily maximum and daily average concentrations of PM2.5, PM10, and CO, where data were available. The day the Station Fire began and the five days following, the period from August 26, 2009, through August 31, 2009, represents the peak period, as concentrations tapered off considerably after this six-day window. Table 1 also presents the number of survey respondents in each surveyed city, and within each city the number and percentage of respondents who smelled smoke and/or ash for the number of days specified in each given range.

To implement the DBM, additional data were gathered on the length of time health symptoms were experienced as a direct result of exposure to the wildfire smoke, as well as the type of symptom experienced. Respondents were asked to report the number of days symptoms were experienced by themselves as well as all household members. Respondents were then presented with a table of potential defensive actions that could have been taken to reduce their exposure to the wildfire smoke. The list of potential defensive actions were chosen based on a number of factors, including recommendations from the CDC on what to do during a fire to decrease exposure to the smoke, recommendations by focus group participants, and finally, the actions that previous studies have confirmed individuals take during wildfires to decrease their exposure (Mott et al. 2002; Kunzli et al. 2006). Given that many defensive actions, such as running an air conditioner, can inherently be taken for reasons other than to prevent wildfire smoke exposure, respondents were specifically told to indicate whether they had taken each action as a direct result of exposure to the wildfire smoke and for no other reason. Respondents were also asked to report the cost of taking each action where this information was applicable. Table 2 outlines the number and percentage of survey respondents who reported taking each defensive action, along with the average cost reported by those respondents who took that action. Eighty-nine percent of respondents took at least one defensive action.

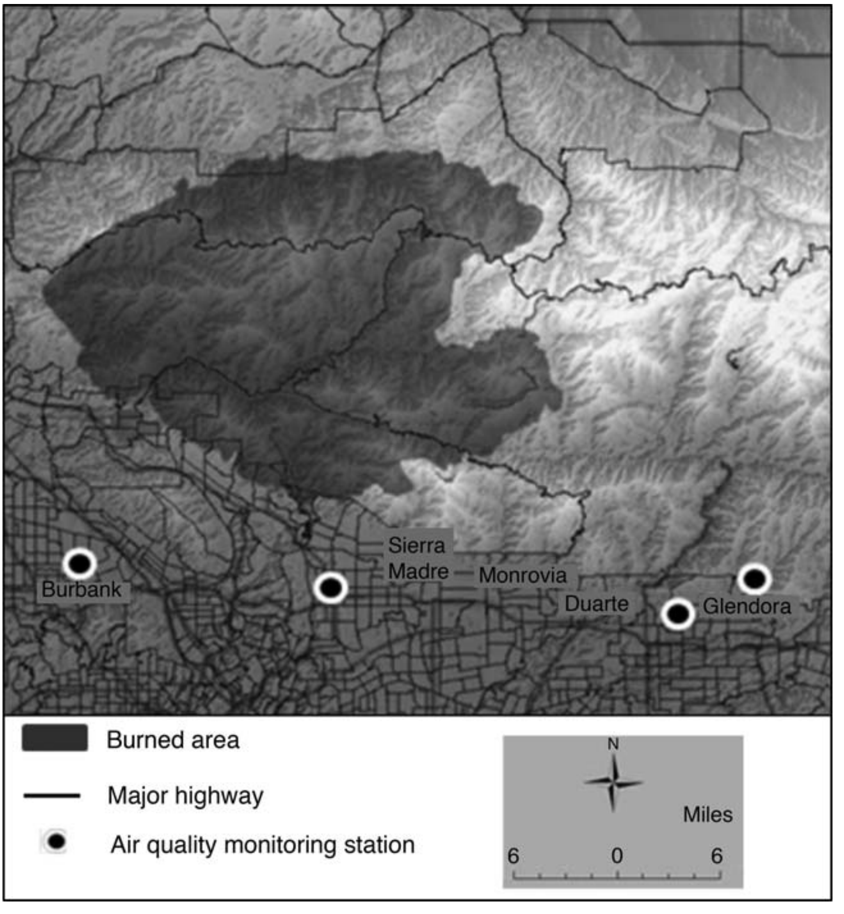

FIGURE 1
Location of Station Fire, Cities Surveyed, and Monitoring Stations
Adapted from: http://seamless.usgs.gov/index.php.

Four respondents reported defensive expenditures well above the sample 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.

To facilitate the quantification of a COI estimate for each individual, only those respondents who experienced health symptoms as a result of exposure to the wildfire smoke were asked an additional set of questions about the medical care they received and the private, out-of-pocket costs incurred for this treatment. They were also asked to report the time spent traveling to, waiting for, and receiving any medical care. In addition, respondents were asked to report any expenditure on nonprescription medications taken to alleviate symptoms, as well as the number of work and/or recreation days missed as a direct result of these symptoms. Elicited in this way, these costs of illness represent an exogenous outcome of the illness experienced and are thus distinct from defensive actions, which are chosen by the individual. This distinction has been the source of some confusion in the literature, as explained in Bockstael and McConnell (2007). Table 3 outlines the number and percentage of survey respondents who undertook these remedial actions, along with

TABLE 1

Objective and Subjective Pollution Levels by City during the Station Fire

City	CO (ppm)		PM2.5 (μg/m^3)		PM10 (μg/m^3)		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	> 5 days	None	1–5 days	> 5 days
Duarte ($n = 54$)	0.68	1.40					18 (33%)	20 (37%)	16 (30%)	2 (4%)	15 (28%)	37 (69%)
Monrovia ($n = 84$)	0.68	1.40					29 (35%)	29 (35%)	26 (31%)	2 (2%)	24 (29%)	58 (69%)
Sierra Madre ($n = 31$)	0.48	1.80					16 (52%)	9 (29%)	6 (19%)	3 (10%)	9 (29%)	19 (61%)
Burbank ($n = 80$)	0.64	1.57	25.18	93.50			37 (46%)	24 (30%)	19 (24%)	4 (5%)	28 (35%)	48 (60%)
Glendora ($n = 164$)	0.65	1.42	46.83	120.83	53.82	133.12	75 (46%)	56 (34%)	33 (20%)	11 (7%)	61 (37%)	92 (56%)

Note: 6-d mean represents six-day averages from the period August 26–August 31, 2009.

the average cost reported. Respondents were also asked a series of questions about their health history, various lifestyle factors, and demographic information.

For the CVM model, only those respondents who experienced health symptoms themselves or had household members experiencing symptoms from the Station Fire smoke were asked an additional question about their WTP to reduce the symptom days their household experienced by 50%. Respondents were told that they would be asked a question about what it would have been worth to them to reduce some of the effects their household may have experienced as a result of wildfire smoke exposure. They were specifically instructed to focus on the health effects experienced, the preventative actions taken to avoid these health effects, as well as days of work and recreation lost as a direct result of smoke from the wildfire when answering the question. While there are many other negative impacts of wildfire, such as damage to the home and amenity effects such as reduced visibility from wildfire smoke, respondents were specifically asked not to consider any of these additional effects. This was done in an effort to make the CVM WTP value as comparable to the DBM WTP value as possible. A dichotomous choice question format was used with 10 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). This type of WTP question format was utilized due to the desirable incentive compatibility properties it has. Survey respondents are presented with only one bid amount and therefore cannot easily influence potential outcomes by purposely revealing values other than their true WTP (Haab and McConnell 2002; Boyle 2003). A summary of all study variables can be found in Table 4. Table 5 identifies the percentage of "yes" responses to the WTP question at each bid amount.

VI. ECONOMETRIC ESTIMATION

Defensive Behavior Model

To implement the DBM to calculate the mean WTP for a reduction in symptom days,

TABLE 2
Defensive Actions Taken by Respondents and Average Expenditure on Each ($N = 413$)

Defensive Actions	Percentage of Survey Respondents	Average Expenditure
Evacuated	5.6%	$257.95
Wore a face mask	7.0%	$6.04
Used a home air cleaner	21.3%	$26.93
Avoided going to work	4.6%	$219.41[a]
Removed ashes from property	57.4%	$8.67
Ran air conditioner more than usual	60.3%	$27.66[b]
Stayed indoors more than usual	73.1%	N/A
Avoided normal outdoor recreation/exercise	77.7%	N/A

Note: N/A, not available.
[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 defensive action). According to the California Energy Commission, the average California resident uses 27 kW-h to run his or her 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/kW-h 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.

TABLE 3
Remedial Actions Taken by Respondents and Average Expenditure on Each ($N = 413$)

Remedial Actions	Percentage of Survey Respondents	Average Expenditure
Obtained medical care/prescription medications	6.3%	$77.87[a]
Took nonprescription medicines	12.6%	$16.86
Went to a nontraditional healthcare provider	1.2%	$33.00
Missed work	3.6%	$691.76
Missed days of recreation activities	27.6%	N/A

Note: N/A, not available.
[a] 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).

a health production function such as that in equation [2] is estimated. The health outcome experienced is the dependent variable of 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 pollution levels, defensive actions taken, the individual's health history, lifestyle factors, and demographics.

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 defensive action 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 have expressed the importance of this issue (Gerking and Stanley 1986; Joyce, Grossman, and Goldman 1989; Alberini et al. 1996; Dasgupta 2004; Dickie 2005).

The dependent variable in this analysis is count in nature (the number of days symptoms were experienced). The potentially endogenous defensive action variables are binary, meaning nonlinear estimation techniques to

TABLE 4
Study Variables and Summary Statistics

Variable	Coding	Mean	Std. Dev.
Perceived Pollution Levels			
Smelled smoke indoors > 5 days	1 = yes, 0 = no	0.24	0.43
Smelled smoke outdoors > 5 days	1 = yes, 0 = no	0.62	0.49
Objective Pollution Levels			
Average daily maximum CO concentration	Parts per million (ppm)	1.47	0.11
Illness Information			
Symptom days	Count	3.28	6.06
Ear, nose or throat symptoms	1 = yes, 0 = no	0.36	0.48
Breathing symptoms	1 = yes, 0 = no	0.18	0.39
Heart symptoms	1 = yes, 0 = no	0.04	0.20
Other symptoms	1 = yes, 0 = no	0.09	0.28
Household symptom days	Count	5.94	9.35
Number of household members with symptoms	Count	0.89	1.24
Averting Actions			
Evacuated	1 = yes, 0 = no	0.06	0.23
Wore a face mask	1 = yes, 0 = no	0.07	0.26
Used a home air cleaner	1 = yes, 0 = no	0.21	0.41
Avoided going to work	1 = yes, 0 = no	0.05	0.21
Removed ashes from property	1 = yes, 0 = no	0.57	0.50
Ran air conditioner more than usual	1 = yes, 0 = no	0.60	0.49
Stayed indoors more than usual	1 = yes, 0 = no	0.73	0.44
Avoided normal outdoor recreation/exercise	1 = yes, 0 = no	0.78	0.42
Mitigating Actions			
Obtained medical care/prescription medications	1 = yes, 0 = no	0.06	0.24
Took nonprescription medications	1 = yes, 0 = no	0.13	0.33
Went to a nontraditional healthcare provider	1 = yes, 0 = no	0.01	0.11
Missed work	1 = yes, 0 = no	0.04	0.19
Missed days of recreation activities	1 = yes, 0 = no	0.28	0.45
Health History			
Current respiratory condition	1 = yes, 0 = no	0.12	0.32
Current heart condition	1 = yes, 0 = no	0.09	0.28
Experienced health effects from wildfire smoke in past	1 = yes, 0 = no	0.24	0.42
Health and Lifestyle			
Times per week of exercise	0 = 0 times/week; 1 = 1–2 times/week; 2 = 3–5 times/week; 3 = > 5 times/week	1.62	0.92
Smoker	1 = yes, 0 = no	0.08	0.28
Alcoholic drinks per week	0 = none; 1 = 1–7 drinks/week; 2 = 8–14 drinks/week; 3 = > 14 drinks/week	0.60	0.73
Current health is excellent	1 = yes, 0 = no	0.29	0.45
Current health is good	1 = yes, 0 = no	0.55	0.50
Current health is fair	1 = yes, 0 = no	0.14	0.35
Current health is poor	1 = yes, 0 = no	0.02	0.14

(table continued on following page)

TABLE 4
Study Variables and Summary Statistics *(continued)*

Variable	Coding	Mean	Std. Dev.
Hours per week of indoor recreation	Continuous	2.95	5.89
Hours per week of outdoor recreation	Continuous	4.95	7.11
Has a regular doctor	1 = yes, 0 = no	0.89	0.31
Demographics			
Male	1 = male, 0 = female	0.60	0.49
Married	1 = yes, 0 = no	0.69	0.46
Age	Continuous	59.11	15.37
White	1 = yes, 0 = no	0.79	0.41
Graduate school graduate	1 = yes, 0 = no	0.20	0.40
College/technical school graduate	1 = yes, 0 = no	0.62	0.49
Employed full-time	1 = yes, 0 = no	0.48	0.50
Employed part-time	1 = yes, 0 = no	0.08	0.27
Not employed	1 = yes, 0 = no	0.42	0.49
Has health insurance	1 = yes, 0 = no	0.92	0.27
Number of children under 18 years old in household	Continuous	0.43	0.83
Lives in Duarte	1 = yes, 0 = no	0.13	0.34
Lives in Monrovia	1 = yes, 0 = no	0.20	0.40
Lives in Sierra Madre	1 = yes, 0 = no	0.08	0.26
Lives in Burbank	1 = yes, 0 = no	0.19	0.40
Lives in Glendora	1 = yes, 0 = no	0.40	0.49
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
Beliefs			
Heard or read about possible health effects	1 = yes, 0 = no	0.86	0.35
Believes smoke can affect health	1 = yes, 0 = no	0.90	0.31

TABLE 5
"Yes" Responses by Bid Amount ($N = 157$)

Bid Amount	N	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

address this issue of endogeneity must be employed. To test for endogeneity of the defensive action variables, we use a version of the Hausman specification error test (see Hausman 1976; Gujarati 2003).[2] Results indicate

[2] Preliminary analysis shows that only three defensive actions, "Used a home air cleaner," "Ran air conditioner more than usual," 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 "Months at current zip code," "Income," "Employed full-time," and "Believes smoke can affect health."

that "Used a home air cleaner" is the only defensive action variable that has a negative and statistically significant effect on the expected number of symptom days, and is also endogenous. Air cleaners and purifiers are recommended in the home during wildfires to help reduce indoor particle levels (Lipsett et al. 2008; USEPA 2010a). Henderson, Milford, and Miller (2005) conducted a study on the effectiveness of air cleaners during wildfires and prescribed burns and found that homes with air cleaners experienced 63% to 88% less particulate matter in the home than those without air cleaners. 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.

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, 2006b).[3] The model has the following equations for the count dependent variable "Symptom days" and the binary endogenous regressor "Used a home air cleaner":

$$\Pr[Y_i = y_i \mid \mathbf{x}_i, d_i, l_i] = f(\mathbf{x}_i{}'\beta + \gamma d_i + \lambda l_i), \quad [16]$$

$$\Pr[d_i = 1 \mid \mathbf{z}_i, l_i] = g(\mathbf{z}_i{}'\alpha + \delta l_i). \quad [17]$$

In the health outcome equation [16], y_i represents the total number of days that symptoms from exposure to the wildfire smoke were experienced, and $\mathbf{x}_i$ represents a vector of exogenous variables that could affect the number of symptom days experienced, such as objective or subjective pollution levels, the type of symptom experienced, health history, demographics, and lifestyle factors, with associated parameters β. The binary endogenous regressor, "Used a home air cleaner," is represented by d_i, with associated parameter γ. Finally, l_i represents latent factors that can affect the decision to use a home air cleaner, as well as the number of symptom days experienced, with associated parameters λ. These latent factors capture the unobserved heterogeneity that is the cause of endogeneity in the model.

"Used a home air cleaner" is modeled in equation [17] where $\mathbf{z}_i$ represents a vector of exogenous variables that could affect the probability that a home air cleaner is used, with associated parameters α. These could be pollution levels, the type of symptom experienced, health history, demographics, lifestyle factors, as well as beliefs about the effects of wildfire smoke on health. Again, this equation includes latent factors l_i with associated parameters δ.

Equations [16] and [17] can contain the same set of exogenous variables; however, for more robust identification, instrumental variables that are included in the equation for "Used a home air cleaner" but excluded from the equation for "Symptom days" can be used. The error term in each equation is partitioned into latent factors l_i and an independently distributed random error term. The joint distribution of "Symptom days" and "Used a home air cleaner" can then be specified, conditional on these common latent factors. While the latent factors are unknown, it is assumed that they come from a normal distribution, allowing them to be integrated out of the joint density. These equations are then estimated jointly by simulation-based estimation. "Symptom days" is modeled with a negative binomial distribution, given the presence of overdispersion in the data, and "Used a home air cleaner" is assumed to follow a normal distribution. Two thousand simulation draws are used based on recommendations from Deb and Trivedi (2006a), and robust standard errors that take simulation error into account are reported. The results of this model, including only those variables that had a statistically significant effect on expected symptom days, can be found in Table 6.[4]

As expected, perceived pollution levels as measured by whether smoke was smelled both inside and outside the home for greater than five days has a positive and statistically significant effect on the expected number of

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

[4] The results of the full model are available from the authors.

TABLE 6
Defensive Behavior Model

Variable	Coef.	Robust Std. Err.
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
Used a 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/technical school 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
Used a Home Air Cleaner, Probit Regression		
Smelled smoke indoors > 5 days	0.362	0.259
Smelled smoke outdoors > 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/technical school graduate	0.375	0.248
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
Income	− 0.005**	0.003
Believes smoke can affect health	1.426**	0.703
Constant	− 3.481***	1.096
/λ (latent factor)	0.858***	0.072
/ln α	− 13.657***	2.491
N	377	
Log likelihood	− 672.066	
Wald χ^2 (24)	424.71	
Prob > χ^2 =	0.0000001	

* $p \le 0.10$; ** $p \le 0.05$; *** $p \le 0.01$.

symptom days experienced, all else constant. Similarly, based on a questionnaire of high school students and children during the 2003 California wildfires, Kunzli et al. (2006) found that the risk of experiencing all health symptoms increased monotonically with perceived pollution levels, as measured by the number of reported smoky days. In addition, we find that having ear, nose, or throat symptoms, breathing symptoms, or other symptoms during the wildfire has a positive and statistically significant effect on the expected number of symptom days, compared to having heart symptoms. Using a home air cleaner is the one defensive action that is found to have a negative and statistically significant effect on expected symptom days. This finding is consistent with prior research (Mott et al.

2002; Henderson, Milford, and Miller 2005). Being a male or married has a negative effect on expected symptom days, compared to individuals who are female or single. Expected symptom days increase with age, which is not surprising given warnings by the CDC and EPA that older individuals are at greater risk of experiencing health effects from exposure to wildfire smoke.

Various factors also have an influence on whether an air cleaner was used in the home to reduce exposure to the smoke from the Station Fire. 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 wildfire smoke exposure may realize this, and as a result they may be more likely to take defensive actions, such as using an air cleaner in their home during a wildfire.

Contingent Valuation Model

In applying a CVM framework to value a decrease in the number of symptom days experienced from exposure to a pollutant, WTP will be a function of the bid amount and any variables that would enter the health production function. The CVM 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 number of symptom days experienced by any member of the household by 50%.

Ultimately, we would like to know the actual WTP 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 that respondent's actual WTP is greater than or equal to this value, or responded "no," in which case the actual WTP is less than this value. Thus, the actual underlying WTP distribution of interest, which we refer to as *WTP**, is unknown. Following closely the work of Alberini (1995), a linear WTP model can be specified as

$$WTP_i^* = \mathbf{x}_i{}'\beta + \varepsilon_i, \qquad [18]$$

where $\mathbf{x}_i$ represents a vector of independent variables that could influence the individual's WTP, 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 equal to the probability that the random WTP function is greater than that offered bid amount:

$$\Pr(WTP_i^* \geq bid_i \,|\, \mathbf{x}_i{}') = 1 - F(bid_i \,|\, \mathbf{x}_i{}'), \qquad [19]$$

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 WTP distribution. Various probability distributions were considered to model WTP; 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 CVM 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 WTP values. Second, assuming a nonnegative distribution for WTP 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 WTP value would indicate that the average individual would actually pay to be sick. The log of the bid amount is included in the model to restrict WTP values to lie between zero and infinity. Assuming WTP follows this log-normal distribution, the WTP model can be specified as

$$WTP_i^* = \exp(\mathbf{x}_i{}'\beta + \varepsilon_i), \qquad [20]$$

and the probability of individual i responding "yes" to a specified bid amount "bid_i" becomes

$$\Pr(WTP_i^* \geq bid_i \mid \mathbf{x}_i{}') = 1 - F(bid_i \mid \mathbf{x}_i{}') = 1 - \Phi\left(\frac{ln(bid_i) - \mu}{\sigma}\right), \qquad [21]$$

where WTP^* is the log of WTP, Φ is the standard normal cumulative distribution function, μ and σ are, respectively, the mean and standard deviation of the log transformation of WTP. 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

$$ln\ L = \sum_{i=1}^{n}\left\{(WTP_i) ln\left[1 - \Phi\left(\frac{ln(bid_i) - \mu}{\sigma}\right)\right] + (1 - WTP_i)\, ln\ \Phi\left(\frac{ln(bid_i) - \mu}{\sigma}\right)\right\}. \qquad [22]$$

A probit regression model is estimated to model the determinants of the predicted probability that the individual is willing to pay the specified bid amount. An additional variable controlling for the number of individuals in the household who experienced symptoms is added to this model. 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. A test down approach is implemented to arrive at the final reduced model, eliminating variables one at a time that do not have a statistically significant effect on the predicted probability that the individual is willing to pay the specified bid amount. The results of this reduced regression model can be found in Table 7.[5,6]

The bid coefficient in this model is negative and statistically significant at the 1% level, indicating that the higher the bid amount, the less likely the individual is willing to pay, all else constant. This provides evidence of theoretical construct validity to the CVM 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 WTP increases with household symptom days, but at a decreasing rate. This is similar to findings by Alberini et al. (1997), Johnson, Fries, and Banzhaf (1997), Liu et al. (2000), and Dickie and Messman (2004). Individuals with a current heart disease are also more likely to be willing to pay the specified bid amount, and this variable is significant at the 10% level.

Turning to lifestyle and demographic factors, we find that being a college or technical school graduate has a positive and significant effect on WTP compared to those respondents without 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 Duarte or Burbank has a positive and significant effect on WTP compared to living in Monrovia, Sierra Madre, or Glendora. 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 WTP.

VII. BENEFIT ESTIMATES FOR A REDUCTION IN ONE WILDFIRE SMOKE–INDUCED SYMPTOM DAY

Defensive Behavior Method WTP

In the DBM regression model, the individual WTP for a given change in illness dS can be calculated as $-[p_d/(\partial S/\partial D)]dS$ from equation [13]. Given that using a home air cleaner is the only defensive action found to have a statistically significant effect on symptom days, the WTP 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 symp-

[5] For comparison purposes, a logit, normal, and log-logit model were also estimated. The Akaike and Bayesian information criterion confirm that the log-normal and log-logit models are superior to the linear in bid models, and the log-logit and log-normal models are virtually identical in fit.

[6] The results of the full model are available from the authors.

TABLE 7
Probit Regression of WTP for 50% Reduction in Symptom Days

Variable	Coef.	Std. Err.
ln(Bid amount)	− 0.455***	0.095
ln(Half of household symptom days)	0.338**	0.156
Current heart condition	0.695*	0.365
College/technical school graduate	0.666**	0.286
Has health insurance	− 1.093***	0.391
Lives in Duarte	0.687**	0.343
Lives in Burbank	0.546*	0.294
Constant	1.201**	0.575
N	157	
Log likelihood	− 78.873	
Likelihood ratio χ^2 (7)	45.610	
Prob $> \chi^2$	0.0000001	

* $p \le 0.10$; ** $p \le 0.05$; *** $p \le 0.01$.

tom days by 0.31.[7] Taking the average cost reported by those respondents who used an air cleaner in their home during the Station Fire results in an estimated price of $26.93 for this defensive action. The average respondent's WTP for a reduction in one symptom day from exposure to wildfire smoke is equal to − 26.93/ − 0.31 = $86.87.

Issues such as joint production are often raised when considering the validity of the estimated value for a reduction in symptom days using this method. For instance, if the defensive action used in the estimate enters into an individual's utility function directly, rather than just through its effect on symptom days, WTP values may be inflated. However, a few factors work to our advantage when taking this complication into account. As previously mentioned, respondents were asked to report only those actions taken as a direct result of exposure to the Station Fire smoke. In addition, home air cleaners are typically used for the specific purpose of reducing indoor pollution levels. Therefore, there is good reason to believe that the marginal effect of home air cleaner use on expected symptom days is accurately calculated.

[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.

Contingent Valuation Method WTP

One goal of this study is to compare the WTP value estimated by applying the CVM to a simple COI estimate and the WTP value estimated by applying the DBM. Given the assumed log-normal distribution of WTP, the median value can be calculated as

$$E(WTP) = \exp(\mu), \qquad [23]$$

and the expected value as

$$E(WTP) = \exp(\mu + 0.5\sigma^2), \qquad [24]$$

where μ and σ are, respectively, the mean and standard deviation of the logged WTP. Estimates of μ and σ are recovered as follows:

$$E(WTP) = \exp\left[\frac{-\mathbf{x}_i{}'\beta}{\beta_{\text{lnbid}}} + 0.5\left(-\frac{1}{\beta_{\text{lnbid}}}\right)^2\right]. \qquad [25]$$

By setting all independent variables at their sample mean, the WTP to avoid an average number of symptom days experienced in the household can be estimated. This results in a value of $400 to avoid an average of seven symptom days, or $57 per day. Plugging in one symptom day and setting all other independent variables at their average value results in a mean WTP value of $95.03 for a reduction in one wildfire smoke–induced symptom day. This is the value focused on for the comparison across methods. Due to the fact that WTP is increasing at a decreasing rate in symptom days, the WTP to avoid one symptom day is much larger than the WTP per day to avoid an average of seven symptom days. This is consistent with previous studies such as that by Alberini et al. (1997), who found that WTP per day to avoid a five-day illness was about one-third the WTP to avoid a one day illness.

Calculating a median estimate of WTP results in a much smaller value of $8.51 to avoid one day of symptoms. A positively skewed distribution of WTP in this health valuation context has been observed in studies such as those by Loehman et al. (1979) and Dickie et al. (1987). This likely indicates the presence of significant variation in tastes and preferences across the population. We continue to focus on the mean WTP measure of central tendency, given that the majority of previous studies comparing CVM WTP values with either DBM WTP values or COI estimates have focused on mean CVM WTP values to make this comparison (see Rowe and Chestnut 1985; Dickie et al. 1986; Berger et al. 1987; Dickie et al. 1987; Chestnut et al. 1996, 2006), and one focus of this study is comparing our findings to theirs. In addition, efforts to recover total population benefit estimates require sample mean WTP values.

While these estimates represent the WTP 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. Given that having health insurance has a negative and highly significant effect on the probability that the individual is willing to pay the specified bid amount, it would be interesting to compare WTP values for those individuals with and without insurance. However, given the very small sample size of respondents without insurance who were eligible to respond to the stated preference question, we do not make this comparison here.

Cost of Illness

To calculate a traditional COI estimate (COI_{trad}) from the sample of survey respondents, those individuals who experienced health symptoms from exposure to the Station Fire smoke are the focus for the analysis. The direct and indirect costs incurred by each individual as a result of these symptoms are totaled. This includes expenditures on medical visits and prescribed medications, expenditures on nonprescription medications, expenditures on visits to a nontraditional healthcare provider, lost wages, as well as the opportunity cost of time spent obtaining medical care, valued at the individual's wage rate. For each individual, this total COI is divided by the number of symptom days experienced to arrive at a daily COI estimate. Taking the average across the sample of respondents who experienced symptoms, results in a COI per symptom day of $3.02, with a median estimate of $0. This is consistent with the discrepancy between mean and median CVM WTP estimates. It should be noted that the medical costs used in these calculations represent private, out-of-pocket costs of treatment paid by the patient and do not include costs incurred by insurance providers.

Taking this calculation one step further to arrive at a comprehensive COI estimate (COI_{comp}), the value of lost recreation is incorporated into the estimate. For each individual who experienced health symptoms from wildfire smoke exposure, the number of days of recreation that individual missed as a direct result of these symptoms is multiplied by the average consumer surplus per day of sightseeing in the Pacific coast region, estimated to be $20.27 based on four previous study estimates (see Loomis 2005). While there are many estimates of the value of various recreational activities provided in the literature, the activity of sightseeing was chosen for a number of reasons. First, the Public Opinions and Attitudes Survey of 2007 found that in general Californians participate in recreation activities that are inexpensive and require little equipment and technical expertise. Of the top 15 recreational activities participated in, sightseeing was ranked second by participation of those individuals surveyed (California

Department of Parks and Recreation 2009). While walking for fitness or pleasure was ranked first, there are no value estimates for this recreational activity found in the literature. Second, the average age of the Station Fire survey respondents that experienced health effects and lost recreation days as a result was 54 years with a maximum age of 89. Therefore, sightseeing is likely a reasonable activity to capture the lost recreation value to the full range of survey respondents. Incorporating this value into each individual's total COI and dividing by the number of symptom days experienced results in an average comprehensive COI per symptom day of $16.87 (median of $13.51).

Comparison of Values

The mean CVM WTP value and marginal DBM WTP value are around 30 times larger than the traditional COI estimate and more than five times larger than the comprehensive COI estimate for a reduction in one symptom day. These ratios of WTP:COI are greater than that found in the majority of previous studies that have compared the two. However, this is the only study to calculate this ratio for the specific case of wildfire smoke exposure using primary data. In addition, while only 20 individuals surveyed sought traditional or nontraditional medical care as a result of symptoms, 366 of these individuals took costly defensive actions to protect themselves from exposure to the wildfire smoke. Further, of the 156 respondents who experienced health symptoms, 110 of them missed recreation days as a result of these symptoms. The disutility associated with symptoms or lost recreation captured in the WTP estimate but not the traditional COI estimate may be substantial for individuals exposed to wildfire smoke. Similar to what theory would predict, incorporating the value of lost recreation into the COI estimate reduces the ratio of WTP to COI considerably.

The daily WTP values of $86.87 and $95.03 fall within those estimated in the literature for other air pollutants. Johnson, Fries, and Banzhaf (1997) summarized a number of studies estimating WTP values for a reduction in various health symptoms and found that

TABLE 8

Values for Reduction in One Wildfire Smoke–Induced Symptom Day

Method	Point Estimate	90% CI
COI_{trad}	$3.02	[$1.63–$4.41]
COI_{comp}	$16.87	[$14.11–$19.62]
Defensive behavior WTP	$86.87	[$76.56–$443.26]
Contingent valuation WTP	$95.03	[$22.78–$610.42]

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.[8]

To explore whether our point estimates of WTP and COI are statistically different, Table 8 presents the estimates of the value for a reduction in one wildfire smoke–induced symptom day, along with the 90% percentile confidence intervals from 1,000 bootstrapped coefficients for the WTP models and standard confidence intervals around the mean COI estimates. The 90% confidence interval of $1.63 to $4.41 around the traditional COI estimate does not overlap the 90% confidence intervals around the WTP values. The null hypothesis that this estimate equals either of the WTP values can be rejected at the 90% confidence level. While the confidence interval around the comprehensive COI estimate of $14.11 to $19.62 is much closer to overlapping the interval around the mean CVM WTP estimate, the null hypothesis that this COI estimate equals either of the WTP values can also be rejected at the 90% confidence level. However, in making this comparison between WTP and COI estimates, a few properties of the WTP measures warrant further discussion. As explained by Haab and McConnell (2002), three sources of randomness in a WTP measure may be present: randomness of preferences, randomness of estimated parameters,

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

and variation across the sample of individuals. The wide bounds on the confidence intervals around the WTP measures indicate high variability across individuals in the sample, although the relatively small sample sizes are undoubtedly also a factor in the large confidence intervals. Nonetheless, these sources of randomness should be recognized when considering the difference between WTP and COI estimates.

Turning to the comparison of the two WTP point estimates, the confidence intervals overlap at even the 90% 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, as it has been shown to result in a lower likelihood of type II error than comparison of confidence intervals. This test results in a one-sided p-value of 0.31 and a two-sided p-value of 0.62. This confirms the comparison of confidence intervals, and we conclude that the null hypothesis of equality of the two WTP point estimates cannot be rejected at standard significance levels. It should be noted that the CVM WTP value is estimated as a discrete change and the DBM WTP value is estimated as a marginal change, which could create some disparity between the two.

VIII. 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 EPA often attempt to quantify the cost imposed on individuals as a result of this exposure. While it is recognized that estimates from a COI approach will often underestimate the economic value of reduced damages to human health, they will continue to be used if there are no other value estimates in the literature.

This study attempts to fill this gap by quantifying the individual value of a reduction in one wildfire smoke–induced symptom day by applying two nonmarket valuation approaches. Using data on the defensive actions individuals reported taking during California's Station Fire of 2009 along with their associated costs, the DBM application reveals that individuals are willing to pay an average of \$86.87 for a reduction in one symptom day. The results of a CVM question reveal that individuals are willing to pay on average \$95.03 for a reduction in one symptom day. Comparing these values to a commonly monetized COI estimate reveals that for the case of wildfire smoke exposure, WTP values can be up to 30 times larger than a traditional COI estimate and up to five times larger than a more comprehensive COI estimate that incorporates the value of lost recreation. Analysis of confidence intervals reveals that while the mean CVM WTP value and marginal DBM WTP are statistically different from the COI estimates, they are not statistically different from one another. The complete combinatorial test further confirms this finding. This result is promising for future applications of both the CVM and DBM in the realm of valuation of health damages, as it provides a test of convergent validity between the two measures.

As this is the first study to estimate WTP values and a WTP:COI ratio for the specific case of reduced health damages from wildfire smoke exposure, these findings could be useful in a benefit transfer context. WTP values estimated in this study could be applied to future wildfires with similar characteristics to the Station Fire in terms of location, size, length of time until containment, effects on human health, and so on. However, care would have to be taken to ensure the accuracy of such a value transfer. The cost of human health damages from exposure to wildfire smoke is one component of the full cost of wildfire damages. Incorporating these monetized values into comprehensive cost estimates of a given wildfire can help inform objective analyses of the appropriate level of funding for fire prevention practices such as prescribed fire and forest thinning. In addition, if policy makers use COI estimates to quantify the cost of health damages from wildfire smoke, applying a conservative calibration factor of five found in this study may more accurately reflect the true value of these damages for the specific case of wildfire smoke exposure than applying ratios found in the literature specific to other pollutants.

Future studies should continue to compare WTP values to COI estimates for the specific case of wildfire smoke exposure to test whether the ratios estimated here are fairly consistent across wildfires. This could provide agencies with greater confirmation of the degree of understatement in benefit estimates typically associated with using a COI estimate. We also recommend that agencies incorporate less traditional costs associated with health symptoms such as the value of lost recreation when using a COI estimate, as this will bring the estimate closer to a more comprehensive welfare measure such as WTP. This may prove especially important for pollution exposure cases in which a large portion of individuals experience minor symptoms for which they do not seek medical attention. Future surveys could also question individuals about which specific recreation activities were missed as a result of symptoms in an effort to attach an accurate consumer surplus value to this loss. Further, collecting data on attitudes about the most important components of an individual's WTP for symptom day reduction could reveal whether defensive actions or disutility components of symptoms and lost leisure represent a significant economic cost to individuals.

Finally, two limitations to this study should be noted. First, we did not attempt to capture medical costs incurred by insurance providers. Second, while children are often heavily affected by wildfire smoke, it is difficult to apply revealed preference approaches such as the DBM to capture the economic value of reduced health damages imposed on children specifically. However, stated preference approaches could be used to question parents about their WTP to reduce the health effects experienced by children in the household specifically. This could be a valuable area for future research. This information will likely become increasingly important in areas such as California where large wildfires are moving closer to city centers and are no longer confined to rural areas.

Acknowledgments

This paper has greatly benefitted from suggestions received by an anonymous reviewer, and comments received at the American Agricultural Economics Association meetings, University of Colorado Environmental and Resource Workshop, and W2133 Regional Research Station 2010 meetings. Partial funding was provided by the Agricultural Experiment Station, Colorado State University.

References

Abt, Karen L., Robert J. Huggett, Jr., and Thomas P. Holmes. 2008. "Designing Economic Impact Assessments for USFS Wildfire Programs." In *The Economics of Forest Disturbances: Wildfires, Storms, and Invasive Species,* ed. Thomas P. Holmes, Jeffrey P. Prestemon, and Karen L. Abt, 151–166. New York: Springer.

Alberini, Anna. 1995. "Optimal Designs for Discrete Choice Contingent Valuation Surveys: Single-Bound, Double-Bound, and Bivariate Models." *Journal of Environmental Economics and Management* 28 (3): 287–306.

Alberini, Anna, and Joseph Cooper. 2000. *Applications of the Contingent Valuation Method in Developing Countries: A Survey.* FAO Economic and Social Development Paper 146. Rome: Food and Agriculture Organization of the United Nations.

Alberini, Anna, Maureen Cropper, Tsu-Tan Fu, Alan Krupnick, Jin-Tan Liu, Daigee Shaw, and Winston Harrington. 1997. "Valuing Health Effects of Air Pollution in Developing Countries: The Case of Taiwan." *Journal of Environmental Economics and Management* 34 (2): 107–26.

Alberini, Anna, Gunnar S. Eskeland, Alan Krupnick, and Gordon McGranahan. 1996. "Determinants of Diarrheal Disease in Jakarta." *Water Resources Research* 32 (7): 2259–69.

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

Bartik, Timothy J. 1988. "Evaluating the Benefits of Non-marginal Reductions in Pollution Using Information on Defensive Expenditures." *Journal of Environmental and Economics Management* 15 (1): 111–27.

Berger, Mark C., Glenn C. Blomquist, Don Kenkel, and George S. Tolley. 1987. "Valuing Changes in Health Risks: A Comparison of Alternative Measures." *Southern Economic Journal* 53 (4): 967–84.

Bockstael, Nancy E., and Kenneth E. McConnell. 2007. *Environmental and Resource Valuation with Revealed Preferences.* Dordrecht, The Netherlands: Springer.

Boyle, Kevin J. 2003. "Contingent Valuation in Practice." In *A Primer on Nonmarket Valuation,* ed. Patricia A. Champ, Kevin J. Boyle, and Thomas

C. Brown, 111–69. Boston: Kluwer Academic Publishers.

Butry, David T., D. Evan Mercer, Jeffrey P. Prestemon, John M. Pye, and Thomas P. Holmes. 2001. "What Is the Price of Catastrophic Wildfire?" *Journal of Forestry* 99 (11): 9–17.

California Department of Parks and Recreation. 2009. *California Outdoor Recreation Plan 2008*. Available at www.parks.ca.gov/?page_id = 23880.

Cameron, Trudy A. 1991. "Interval Estimates of Nonmarket Resource Values from Referendum Contingent Valuation Surveys." *Land Economics* 67 (4): 413–21.

Carson, Richard T., Nicholas E. Flores, Kerry M. Martin, and Jennifer L. Wright. 1996. "Contingent Valuation and Revealed Preference Methodologies: Comparing the Estimates for Quasi-public Goods." *Land Economics* 72 (1): 80–99.

Centers for Disease Control and Prevention (CDC). 1999. "Surveillance of Morbidity during Wildfires-Central Florida, 1998." *MMWR Morbidity and Mortality Weekly Report* 48 (4): 78–79.

———. 2008. "Monitoring Health Effects of Wildfires Using the BioSense System: San Diego County, California, October 2007." *MMWR Morbidity and Mortality Weekly Report* 57 (27): 741–47.

Chestnut, Lauraine G., L. Robin Keller, William E. Lambert, and Robert D. Rowe. 1996. "Measuring Heart Patients' Willingness to Pay for Changes in Angina Symptoms." *Medical Decision Making* 16 (1): 65–76.

Chestnut, Lauraine G., Mark A. Thayer, Jeffrey K. Lazo, and Stephen K. Van Den Eeden. 2006. "The Economic Value of Preventing Respiratory and Cardiovascular Hospitalizations." *Contemporary Economic Policy* 24 (1): 127–43.

Cooper, Joseph C. 1994. "A Comparison of Approaches to Calculating Confidence Intervals for Benefit Measures from Dichotomous Choice Contingent Valuation Surveys." *Land Economics* 70 (1): 111–22.

Courant, Paul N., and Richard C. Porter. 1981. "Averting Expenditure and the Cost of Pollution." *Journal of Environmental Economics and Management* 8 (4): 321–29.

Cropper, Maureen L. 1981. "Measuring the Benefits from Reduced Morbidity." *American Economic Review* 71 (2): 235–40.

Dale, Lisa. 2009. *The True Cost of Wildfire in the Western U.S.* Lakewood, CO: Western Forestry Leadership Coalition.

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

Deb, Partha, and Pravin K. Trivedi. 2006a. "Specification and Simulated Likelihood Estimation of a Non-normal Treatment-Outcome Model with Selection: Application to Health Care Utilization." *Econometrics Journal* 9 (2): 307–31.

———. 2006b. "Maximum Simulated Likelihood Estimation of a Negative Binomial Regression Model with Multinomial Endogenous Treatment." *Stata Journal* 6 (2): 246–55.

Dickie, Mark. 2003. "Defensive Behavior and Damage Cost Methods." In *A Primer on Nonmarket Valuation,* ed. Patricia A. Champ, Kevin J. Boyle, and Thomas C. Brown, 395–444. Boston: Kluwer Academic Publishers.

———. 2005. "Parental Behavior and the Value of Children's Health: A Health Production Approach." *Southern Economic Journal* 71 (4): 855–72.

Dickie, Mark, and Shelby Gerking. 1991a. "Valuing Reduced Morbidity: A Household Production Approach." *Southern Economic Journal* 57 (3): 690–702.

———. 1991b. "Willingness to Pay for Ozone Control: Inferences from the Demand for Medical Care." *Journal of Environmental Economics and Management* 21 (1): 1–16.

Dickie, Mark, Shelby Gerking, David Brookshire, Don Coursey, William Schulze, Anne Coulson, and Donald Tashkin. 1987. "Reconciling Averting Behavior and Contingent Valuation Benefit Estimates of Reducing Symptoms of Ozone Exposure." In *Improving Accuracy and Reducing Costs of Environmental Benefit Assessments.* U.S. Environmental Protection Agency, Cooperative Agreement #CR812054-01-2. Washington, DC: National Center for Environmental Economics.

Dickie, Mark, Shelby Gerking, William Schulze, Anne Coulson, and Donald Tashkin. 1986. "Value of Symptoms of Ozone Exposure: An Application of the Averting Behavior Method." In *Improving Accuracy and Reducing Costs of Environmental Benefit Assessments*. U.S. Environmental Protection Agency, Cooperative Agreement #CR812054-01-2. Washington, DC: National Center for Environmental Economics.

Dickie, Mark, and Victoria L. Messman. 2004. "Parental Altruism and the Value of Avoiding Acute Illness: Are Kids Worth More Than Parents?" *Journal of Environmental Economics and Management* 48 (3): 1146–74.

Duclos, Philippe, Lee M. Sanderson, and Michael Lipsett. 1990. "The 1987 Forest Fire Disaster in California: Assessment of Emergency Room Visits." *Archives of Environmental Health: An International Journal* 45 (1): 53–58.

Efron, Bradley. 1979. "Bootstrap Methods: Another Look at the Jackknife." *Annals of Statistics* 7 (1): 1–26.

———. 1982. *The Jackknife, the Bootstrap and Other Resampling Plans*. Philadelphia: Society for Industrial and Applied Mathematics.

Efron, Bradley, and Robert J. Tibshirani. 1993. *An Introduction to the Bootstrap*. New York: Chapman and Hall.

Freeman, A. Myrick. 2003. *The Measurement of Environmental and Resource Values.* 2nd ed. Washington, DC: Resources for the Future Press.

Gerking, Shelby, and Linda R. Stanley. 1986. "An Economic Analysis of Air Pollution and Health: The Case of St. Louis." *Review of Economics and Statistics* 68 (1): 115–21.

Giraud, Kelly L., John B. Loomis, and Joseph C. Cooper. 2001. "A Comparison of Willingness to Pay Estimation Techniques from Referendum Questions." *Environmental and Resource Economics* 20 (4): 331–46.

Grossman, Michael. 1972. "On the Concept of Health Capital and the Demand for Health Care." *Journal of Political Economy* 80 (2): 223–55.

Gujarati, Damodar N. 2003. *Basic Econometrics.* 4th ed. New York: McGraw Hill/Irwin.

Haab, Timothy C., and Kenneth E. McConnell. 2002. *Valuing Environmental and Natural Resources.* Northampton, MA. Edward Elgar Publishing.

Harrington, Winston, Alan J. Krupnick, and Walter O. Spofford, Jr. 1989. "The Economic Losses of a Waterborne Disease Outbreak." *Journal of Urban Economics* 22 (1): 101–12.

Harrington, Winston, and Paul R. Portney. 1987. "Valuing the Benefits of Health and Safety Regulation." *Journal of Urban Economics* 22 (1): 101–12.

Hausman, Jerry A. 1976. "Specification Tests in Econometrics." *Econometrica* 46 (6): 1251–71.

Henderson, David E., Jana B. Milford, and Shelly L. Miller. 2005. "Prescribed Burns and Wildfires in Colorado: Impacts of Mitigation Measures on Indoor Air Particulate Matter." *Journal of the Air and Waste Management Association* 55 (10): 1516–26.

Hole, Arne R. 2007. "A Comparison of Approaches to Estimating Confidence Intervals for Willingness to Pay Measures." *Health Economics* 16 (8): 827–40.

Johnson, F. Reed., Erin E. Fries, and H. Spencer Banzhaf. 1997. "Valuing Morbidity: An Integration of the Willingness-to-Pay and Health-Status Index Literatures." *Journal of Health Economics* 16 (6): 641–65.

Johnston, Fay, Anne Marie Kavanagh, David Bowman, and Randall Scott. 2002. "Exposure to Bushfire Smoke and Asthma: An Ecological Study." *Medical Journal of Australia* 176 (11): 535–38.

Joyce, Theodore J., Michael Grossman, and Fred Goldman. 1989. "An Assessment of the Benefits of Air Pollution Control: The Case of Infant Health." *Journal of Urban Economics* 25 (1): 32–51.

Kochi, Ikuho, Geoffrey H. Donovan, Patricia A. Champ, and John B. Loomis. 2010. "The Economic Cost of Adverse Health Effects from Wildfire-Smoke Exposure: A Review." *International Journal of Wildland Fire* 19 (7): 803–17.

Krinsky, Itzhak, and A. Leslie Robb. 1986. "On Approximating the Statistical Properties of Elasticities." *Review of Economics and Statistics* 68 (4): 715–19.

Kunzli, Nino, Ed Avol, Jun Wu, W. James Gauderman, Ed Rappaport, Joshua Millstein, Jonathan Bennion, Rob McConnell, Frank D. Gilliland, Kiros Berhane, Fred Lurmann, Arthur Winer, and John M. Peters. 2006. "Health Effects of the 2003 Southern California Wildfires on Children." *American Journal of Respiratory and Critical Care Medicine* 174 (1): 1221–28.

Lipsett, Michael, Barbara Materna, Susan Lyon Stone, Shannon Therriault, Robert Blaisdell, and Jeff Cook. 2008. *Wildfire Smoke: A Guide for Public Health Officials.* Available at http://oehha.ca.gov/air/risk_assess/wildfirev8.pdf.

Liu, Jin-Tan, James K. Hammitt, Jung-Der Wang, and Jin-Long Liu. 2000. "Mother's Willingness to Pay for Her Own and Her Child's Health: A Contingent Valuation Study in Taiwan." *Health Economics* 9 (4): 319–26.

Loehman, E. T., S. V. Berg, A. A. Arroyo, R. A. Hedinger, J. M. Schwartz, M. E. Shaw, R. W. Fahien, V. H. De, R. P. Fishe, D. E. Rio, W. F. Rossley, and A. E. S. Green. 1979. "Distributional Analysis of Regional Benefits and Cost of Air Quality Control." *Journal of Environmental Economics and Management* 6 (3): 222–43.

Loomis, John. 2005. *Updated Outdoor Recreation Use Values on National Forests and Other Public Lands*. General Technical Report PNW-GTR-658. Portland, OR: U.S. Department of Agriculture Forest Service, Pacific Northwest Research Station.

Loomis, John, Michael Creel, and Timothy Park. 1991. "Comparing Benefit Estimates from Travel Cost and Contingent Valuation Using Confidence Intervals for Hicksian Welfare Measures." *Applied Economics* 23 (1): 1725–31.

Morton, Douglas C., Megan E. Roessing, Ann E. Camp, and Mary L. Tyrrell. 2003. *Assessing the Environmental, Social, and Economic Impacts of Wildfire*. GISF Research Paper. New Haven, CT:

Yale University Global Institute of Sustainable Forestry.

Mott, Joshua A., Pamela Meyer, David Mannino, Stephen C. Redd, Eva M. Smith, Carol Gotway-Crawford, and Emmett Chase. 2002. "Wildland Forest Fire Smoke: Health Effects and Intervention Evaluation, Hoopa, California, 1999." *Western Journal of Medicine* 176 (3): 157–62.

Poe, Gregory L., Kelly L. Giraud, and John B. Loomis. 2005. "Computational Methods for Measuring the Difference of Empirical Distributions." *American Journal of Agricultural Economics* 87 (2): 353–65.

Poe, Gregory L., Eric K. Severance-Lossin, and Michael P. Welsh. 1994. "Measuring the Difference (X-Y) of Simulated Distributions: A Convolutions Approach." *American Journal of Agricultural Economics* 76 (4): 904–15.

Rowe, Robert D., and Lauraine G. Chestnut. 1985. *Oxidants and Asthmatics in Los Angeles: A Benefits Analysis.* Report to the U.S. Environmental Protection Agency, Office of Policy Analysis, EPA-230-07-85-010, Washington, D.C., March; and Addendum, March 1986. Boulder, CO: Energy and Resource Consultants, Inc.

Studenmund, A. H. 1992. *Using Econometrics: A Practical Guide*. 2nd ed. New York: Harper Collins Publishers.

Tolley, George, Lyndon Babcock, et al. 1986. *Contingent Valuation Study of Light Symptoms and Angina.* Valuation of Reductions in Human Health Symptoms and Risks, Vol. 3. University of Chicago and U.S. Environmental Protection Agency, Grant #CR-811053-01-0.

Um, Mi-Jung, Seung-Jun Kwak, and Tai-Yoo Kim. 2002. "Estimating Willingness to Pay for Improved Drinking Water Quality Using Averting Behavior Method with Perception Measure." *Environmental and Resource Economics* 21 (3): 287–302.

U.S. Environmental Protection Agency (USEPA). 2010a. *Indoor Air Quality: Guide to Air Cleaners in the Home.* Available at www.epa.gov/iaq/pubs/airclean.html#What Types. Updated April 26, 2010.

———. 2010b. *Damage Avoided (morbidity).* National Center for Environmental Economics (NCEE). Available at http://yosemite.epa.gov/ee/epalib/ord1.nsf/8e2804a29538bbbf852565a500502e9e/18811b4089f366ef852565a5006abf11!OpenDocument. Updated Aug. 13, 2010.