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# Wildfire smoke and health impacts: A closer look at fire attributes and their marginal effects

K. Moeltner [a,*], M.-K. Kim [b], E. Zhu [c], W. Yang [d]

[a] *Department of Agricultural and Applied Economics, Virginia Tech, United States*
[b] *Department of Applied Economics, Utah State University, United States*
[c] *Department of Finance, Beijing Language and Culture University, People's Republic of China*
[d] *School of Community Health Sciences, University of Nevada, Reno, United States*

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ABSTRACT

Existing studies on the economic impact of wildfire smoke have focused on single fire events or entire seasons without considering the marginal effect of daily fire progression on downwind communities. Neither approach allows for an examination of the impact of even the most basic fire attributes, such as distance and fuel type, on air quality and health outcomes. Improved knowledge of these effects can provide important guidance for efficient wildfire management strategies. This study aims to bridge this gap using detailed information on 24 large-scale wildfires that sent smoke plumes to the Reno/Sparks area of Northern Nevada over a 4-year period. We relate the daily acreage burned by these fires to daily data on air pollutants and local hospital admissions. Using information on medical expenses, we compute the per-acre health cost of wildfires of different attributes. We find that patient counts can be causally linked to fires as far as 200–300 miles from the impact area. As expected, the marginal impact per acre burned generally diminishes with distance and for fires with lighter fuel loads. Our results also highlight the importance of allowing for temporal lags between fire occurrence and pollutant levels.



## Introduction

Numerous contributions in environmental economics and related fields over recent years have provided evidence of a direct relationship between poor air quality and human health problems. For example, Chay and Greenstone (2003) use variations in air pollution reduction across locations due to the economic recession in the early 1980's to identify the impact of total suspended particulates (TSPs) on infant mortality. They find that a 1% decline in TSP levels resulted in a 0.35% decline in infant mortality rates. Currie and Neidell (2005) examine the impact of air pollution on infant health in California over the 1990s, focusing on the role of ozone ($O_3$), carbon monoxide (CO), and particulate matter ($PM_{10}$). Their main finding is that the reduction in CO that occurred over that decade saved approximately 1000 infant lives in California.

Wildfire smoke can be a major contributor to a deterioration in air quality, triggering a variety of adverse health effects. For example, Jayachandran (2009) examines the impact of the widespread 1997 wildfires in Indonesia on fetal, infant, and child mortality in that region. She finds that wildfire-related pollution led to over 15,000 deaths amongst this target population, or a 1.2% decrease in survival for the affected cohort. Emmanuel (2000) analyzes the health impact of the same

* Corresponding author. Fax: +1 540 231 7417.
*E-mail addresses:* moeltner@vt.edu (K. Moeltner), mk.kim@usu.edu (M.-K. Kim), zhuerqian@blcu.edu.cn (E. Zhu), weiyang@unr.edu (W. Yang).

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fires in neighboring Singapore. She finds a 30% increase in outpatient attendance for haze-related conditions, and a 12% increase in upper respiratory tract illness. Fowler (2003) synthesizes 30 years of research on the human health impacts of forest fires. She concludes that the spectrum of adverse health effects of biomass smoke ranges from temporary eye, nose, and throat irritations, to persistent cardiopulmonary conditions, and even premature death.

Over the last three decades the United States has experienced an increasing trend in public lands consumed by wildfire. In the 1980s close to three million acres burned in an average year. This number increased to 3.6 million in the 1990s, and to over 6.5 million in the 2000s (National Interagency Fire Center, 2012). Annual fire prevention and suppression expenditures have risen commensurately and approached the $3 billion mark in recent years (U.S. Government Accountability Office, 2007). Not surprisingly, the cost-effectiveness of existing fire management strategies has come under close scrutiny with budget offices and legislative units (U.S. Government Accountability Office, 2007; Gebert et al., 2008).

The design of efficient wildfire programs requires an understanding of the "values at risk" or – alternatively put – the expected benefits from preventing or suppressing a fire event (Gebert et al., 2008). These include the economic costs that arise due to the impact of wildfire smoke on human health (Abt et al., 2008; Holmes et al., 2008). Kochi et al. (2010) synthesize the existing studies that have examined the nexus of wildfires, air quality, and illness and conclude that there is still much to be learned about the causal impact of wildfire smoke on health outcomes, especially with respect to the detailed attributes of a specific fire event.

Most existing contributions either consider a single fire event (Butry et al., 2001; Adamowicz et al., 2004; Viswanathan et al., 2006), or air quality changes over an entire fire season without controlling for individual burns (Johnston et al., 2002a, 2002b; Tham et al., 2009). This preempts a closer investigation of the marginal effects of even the most basic fire attributes on smoke-induced illness, such as size, distance, and fuel load. Yet, a better understanding of these margins is needed for the efficient allocation of resources amongst competing fires, fire-prone areas, and values-at-risk. For example, preemptive fuel reduction efforts may be more cost-effective in an area that is upwind from a large population zone, ceteris paribus. The same rationale holds for the allocation of combative resources after a fire has started. Reducing wildfire smoke via such interventions may produce net gains even at a large distance from the impact area. This is supported by our findings.

In addition, most existing studies identify the fire impact on health outcomes by comparison with a baseline period, either immediately preceding and/or following a fire event (Butry et al., 2001; Kochi et al., 2012), or based on the same calendar period from a preceding year (Viswanathan et al., 2006). This exposes the analysis to considerable risk of confounding effects if the baseline and fire periods differ in other relevant dimensions than wildfire smoke production. As argued in Butry et al. (2001) and Kochi et al. (2010) a long-run time series of *daily* observations on fire activity, air quality, and health impacts would be needed to allow for a more robust identification of smoke effects.

This study is the first to compile and analyze such data. We benefit from what could be described as an ongoing natural experiment: the urban area of Reno/Sparks in Northern Nevada traditionally experiences smoke from numerous wildfire events every season. This is due to the typically dry conditions in the Sierra Nevada mountain range and foothills that border this area to the west, and the prevailing north-western to south-western wind patterns. Furthermore, these fires vary significantly in important dimensions. Some of them are as remote as 200–300 miles from the impact area, while others burn at the urban fringe. In addition, fires at any distance vary in fuel composition. They can occur in grassland, the sage/juniper interface, or in large stands of mature timber. Thus, observing these fire events over several seasons provides the necessary variability in distance and fuel load to identify corresponding marginal effects.

At the same time, Nevada state law requires all hospitals to report data on inpatient admissions to research centers at state universities. This information allows us to track daily hospital admissions for illnesses traditionally related to severe air pollution over the same time period as the wildfire occurrences. We then take a Cost-of-Illness (COI) approach relating fire events and attributes to treatment costs (Kochi et al., 2010).

Our research adds to the existing literature in five dimensions: First, by considering multiple and diverse fires over several seasons we are able to estimate marginal effects of basic fire attributes, such as fuel load and distance. Second, the length and seamlessness of our time series allow us to control for confounding air quality and morbidity effects without resorting to a specific "baseline period". Third, our focus on daily acres burned allows for an examination of *lagged* fire effects on air quality, and how they vary over fuel load. Fourth, we propose a tractable and flexible strategy to control for the variability in daily wind direction and speed. Fifth, we report health impacts and costs for different population segments, most notably young children and the elderly, as advocated in Kochi et al. (2010).

Accounting for lagged effects, we find that an additional 100 acres burned cause between $60 and $210 in inpatient treatment costs for acute respiratory problems, depending on fire distance and primary fuel type. The analogous cost estimates for cardiovascular admissions range from $70 to $260. For the 2008 fire season this translates into total smoke-induced inpatient costs in Reno/Sparks of close to $2.2 million.

Our analysis encountered numerous data challenges as daily updates on fire behavior, including spread, fuel type, and intensity, are not yet routinely collected and archived by land managing agencies. In addition, different pieces of fire information are stored in different repositories, in different formats, and/or at different levels of aggregation. Thus, we concur with Abt et al. (2008) that a better understanding of the economic impact of wildfires and the development of efficient management strategies will hinge critically on improved and streamlined wildfire recording and data management.

## Data

### *Wildfire data*

The time frame for our analysis ranges from March 3, 2005 to December 30, 2008, for a total of 1399 days. This is based on the availability of daily data on both air quality and patient admissions. For this time period, we initially considered all individual wildfires of at least 500 acres in size within a 500 mile radius from Reno/Sparks, as listed in the National Interagency Coordination Center (NICC)'s archive of Incident Management Situation (SIT) reports (National Fire and Aviation Management, 2011).[1]

The ultimate aim of our analysis is to relate daily acres consumed by wildfires to measurements of air quality and resultant medical expenditures in the target area. To produce such an impact, wildfire smoke needs to travel from the fire origin to the impact zone. An exact scientific modeling of smoke production and transportation is beyond the scope of this paper and would vastly exceed the limitations of our data. We therefore base a further selection of relevant fire events on the pragmatic assumption that a wildfire, no matter how close to the target area, cannot feasibly affect air quality there if it never falls upwind of the impact zone for its entire activity period. In other words, we define our target population of fires as those that for at least one day of their active status, were located upwind from Reno/Sparks.[2]

To establish wind-related relevance we evaluate the compass location of a given fire relative to the daily resultant wind direction (RDIR) observed for the impact area.[3] Let $R_t$ denote the RDIR on day $t$. We then define deviation $d$, in compass degrees, and examine which wildfires that are active that day fall within $R_t \pm d$. We repeat this for all days in our series (holding $d$ constant) and drop fires from our initial set that fail this criterion for their entire duration. Since RDIR is only a summary measure that may miss significant hourly fluctuations in wind direction, setting $d$ too tight risks omitting relevant fires. Setting $d$ too large would clutter our data with hundreds of irrelevant events.

Fig. 1 illustrates this concept. It depicts an RDIR of 291°, and directional bounds for different values of $d$. The white circles labeled A through C represent fire locations. At $d=30^\circ$ only fire A would contribute what we label as "*effective acres*" that day. At $d=90^\circ$, burned acreage by both A and B would be counted as "effective". Fire C does not contribute any effective acres, even at our most lenient setting of $d=120^\circ$. If this situation persisted for the entire duration of C, the fire would be dropped from our data set. Conversely, A and B would be included, even if this day were the only one during which they contributed effective acres. Further details on our use of the effective acres criterion are given in the next section below.

As discussed below in detail, we choose deviation criteria between $d=30^\circ$ and $d=90^\circ$, depending on fire distance from the impact area. The spatial distribution of the resulting 24 separate fire events is depicted in Fig. 2. Each fire is represented by a solid circle. The size of a given circle symbolizes the total burn size of the underlying fire. Dark circles mark fires that occurred in areas with higher fuel loads, while white circles symbolize fires in ecosystems with lower fuel loads, as discussed further in the empirical section. The map also shows the location of the impact area as well as 50, 100, and 200 mile distance zones, as used in our empirical model below. Not surprisingly, the largest fires occurred in areas with higher fuel loads and/or difficult accessibility, i.e. in the High Sierras just west of Reno and along the Californian coastal range. Lower fuel-load fires tend to be smaller and concentrate in the grass/sagebrush/juniper interface adjacent to and to the north of the impact area.

The figure also depicts a wind rose plot for Reno for the year 2008 (source: Western Regional Climate Center, 2012).[4] The length of each "spoke" around the compass circle is related to the frequency of time the wind blows *from* a particular direction. As is obvious from the plot, the primary wind directions are well-aligned with the majority of fire events for this area.

Details for individual wildfires were obtained from the Western Great Basin Coordination Center (WGBCC) in Reno, Nevada, and the SIT reports mentioned above. Information on the daily acres burned was provided by a GIS specialist at the U.S. Forest Services Pacific Southwest Research Station in Albany, California. We augment and refine this Forest Service data with data from the daily fire tracking web site of the Western Institute for Study of the Environment (W.I.S.E.).[5] For burn days for which information on daily fire growth was not available (approximately 20–30% of fire-days) we estimate the consumed area via interpolation using the nearest known data points.[6]

[1] Holmes et al. (2008) estimate that fires exceeding 500 acres account for 94 percent of all acres burned in the Southern Sierra Nevada between 1910 and 2003.

[2] Naturally, this criterion is itself based on the assumptions that wildfire smoke travels more or less in a straight line. This appears reasonable given that initial fire plumes tend to move with wind direction (Lipsett et al., 2008) and the short temporal lags we consider for our analysis.

[3] The RDIR is computed as an average of hourly wind directions, as measured by the primary eight compass points (e.g. SW, S, and SE). Directions that are logged more frequently over a 24-hour period are receiving relatively higher weight in this aggregate metric. We considered this the most relevant, publicly available wind measure given our research objectives. For the fire season months of May through September, Reno's RDIR fell between 270° (due West) and 290° on 40% of all days, and between 230° and 360° (due North) on 83% of all days. See also the wind rose plot in Fig. 2.

[4] Some of the original annotation to the plot, such as the color legend for wind speed, has been omitted for ease of exposition. We refer the reader to the original version, available from the WRCC web site given in the reference section, for details.

[5] W.I.S.E. is a non-profit educational and research facility with headquarters in Lebanon, Oregon. This agency routinely collects daily fire information for the West and Northwest based on official media reports and updates provided by various federal and State agencies. It then posts the entire daily history for a given fire on its fire tracking web site (Western Institute for Study of the Environment, 2011).

[6] Since wildfires generally receive highest scrutiny at start-up, the burned acreage for the first few days is available for most of our fire events. For some of the shorter and smaller burns (e.g. Crag, Verdi) we spread the total reported acreage upon extinction evenly over the entire duration (usually 2–5 days). Given the small areas involved, this should not have measurable implications for our results.

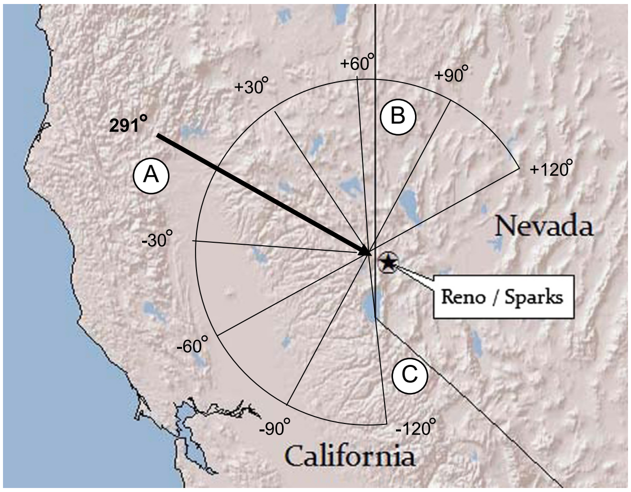


**Fig. 1.** Directional bounds for the identification of wind-relevant fires and effective acres.

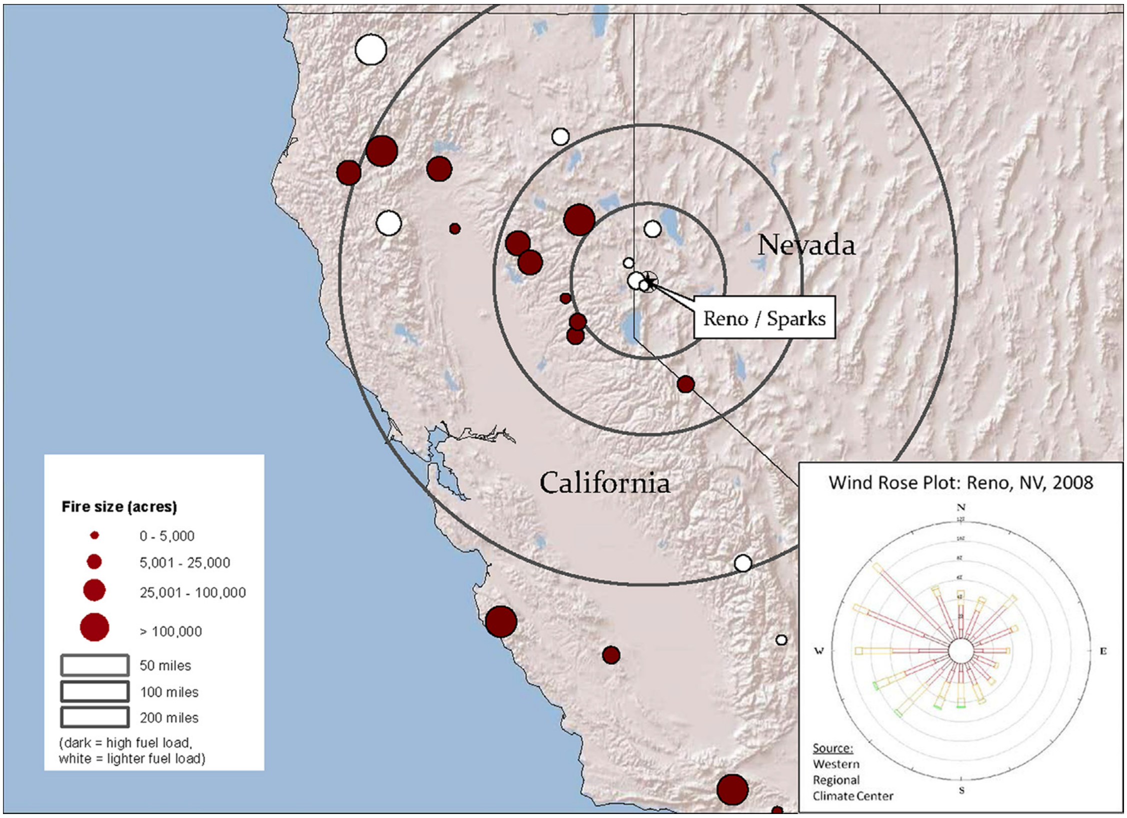


**Fig. 2.** Locations of wildfires and impact area.

Fire details are given in Table A1 in Appendix A. Overall, these burn events consumed over 1.2 million acres over the research period. They range from a size of 700 acres to over 190,000 acres, for an average of 50,200 acres. Some of them were extinguished within a few days, while others burned for many weeks. The mean duration is 31 days. As shown in the last column of the table these fires occurred within a wide radius of Reno/Sparks, from the city limits to a distance of over 350 miles. The average distance is 140 miles.

The last column of the table shows the “primary fuel model” code from the SIT reports. These fuel models are based on the 13 standard categories, each describing a specific ecosystem (see e.g. Anderson, 1982). The primary distinction between fuel categories is their fuel load in tons/acre. The dominant fuel model in our data is 10 “timber with litter and understory”,

**Table 1**
Climate data, Reno/Sparks, 2005–2008.

| Climate variable | Units | Mean | Std | Min | Max |
|---|---|---|---|---|---|
| Avg. temperature | Fahrenheit | 55.28 | 16.59 | 14.00 | 89.80 |
| Min. temperature | Fahrenheit | 40.78 | 13.96 | 3.00 | 73.40 |
| Max. temperature | Fahrenheit | 71.52 | 18.25 | 28.00 | 108.00 |
| Avg. daily dew point | Fahrenheit | 28.00 | 8.52 | −2.40 | 54.80 |
| Avg. wind speed | knots | 5.34 | 3.13 | 0.10 | 22.00 |
| Max. sustained wind speed | Knots | 15.21 | 6.05 | 2.90 | 42.00 |
| Precipitation | Inches | 0.02 | 0.09 | 0.00 | 1.54 |
| Minimum relative humidity | Percent | 22.34 | 14.16 | 3.00 | 89.00 |
| Maximum relative humidity | Percent | 64.89 | 17.51 | 26.00 | 100.00 |
| Avg. daily air pressure | Inches of mercury | 25.59 | 0.14 | 25.05 | 26.06 |

followed by 5 “brush (2 feet)”, and 2 “timber (grass and understory)” (Anderson, 1982). For our econometric analysis below we combine fuel models 4 (12 tons/acre) and 10 (13 tons/acre) into a “high fuel load” category, and the remaining models (ranging from 3–6 tons/acre) into a “low fuel load” category. This binary attribute is captured by the color-coded circles in Fig. 2 above.

### *Air quality and meteorological data*

We follow the bulk of existing studies at the interface of wildfire, air quality, and health and focus on fine particulate matter ($PM_{2.5}$) as the signature pollutant that has been found to cause respiratory problems in impacted areas (e.g. Fowler, 2003; Rittmaster et al., 2006; Viswanathan et al., 2006).[7] Data on average daily levels of $PM_{2.5}$ and other pollutants were obtained via the Washoe County Health District's air quality management reports and data web site (Washoe County Health District, 2011). Daily meteorological data for the Reno/Sparks area were downloaded from the National Climatic Data Center (NCDC)'s data repository site (National Climatic Data Center, 2011). Summary statistics for the meteorological variables used in our econometric models are given in Table 1.

The average daily value for $PM_{2.5}$ for our entire time series is 15.8 $\mu g/m^3$, with a standard deviation of 9.6 $\mu g/m^3$. The 24-hour EPA standard of 35 $\mu g/m^3$ is exceeded on 38 or 2.7% of research days. The annual EPA standard of 15 $\mu g/m^3$ is slightly exceeded in 2006 and 2007, and clearly exceeded in 2008 (annual average = 18.1 $\mu g/m^3$). The daily series is plotted in the center panel of Fig. 3. The graph depicts a clear seasonal pattern with increased $PM_{2.5}$ levels from November through January. This is consistent with the Reno/Sparks basin's inversion pattern that often traps polluted air during the cold season. In addition, more particulate matter is released during that time through domestic wood burning.

The bottom panel of Fig. 3 plots daily effective acres from all fires using as an example a $d=90^\circ$ deviation criterion, which emerges as the preferred setting from our empirical analysis for fires beyond a 100 mile radius (see below). As is evident from the figure, the total number of daily effective acres burned ranges from a few hundred to close to 40,000. There also appears to be a pattern of increasingly severe fire seasons over time, with the summer of 2008 marking the worst season in California since record keeping started in the 1970's.

Importantly for our research, a comparison between the bottom and center panel shows a clear temporal correspondence of elevated $PM_{2.5}$ levels and effective acres burned. This correlation is especially apparent during the record 2008 fire season, with $PM_{2.5}$ levels reaching peaks of 140 $\mu g/m^3$ and higher.

### *Hospital data*

Patient admissions data were provided by The Center for Health Information Analysis (CHIA) at the University of Nevada, Las Vegas, and the Nevada Center for Health Statistics and Informatics at the University of Nevada, Reno. Under state law, these Centers collect and maintain billing records from Nevada hospital and ambulatory surgical centers. Among other information, these medical outfits are required to submit daily inpatient data to these Centers on a regular basis.

The existing literature provides evidence that wildfire smoke is primarily related to two types of morbidity outcomes: respiratory illness (including asthma) and cardiovascular disease (Phonboon et al., 1999; Emmanuel, 2000; Fowler, 2003; Delfino et al., 2009; Kochi et al., 2010). Accordingly, we consider all *unscheduled* inpatient (i.e. overnight) visits related to respiratory disease as captured by International Disease Codes (IDCs) 460.0–486.99, and 488.0–519.99, except for influenza (IDC 487.00–487.99). With respect to cardiovascular ailments, we include acute myocardial infarction and stroke (ICD codes 410.00–410.99 and 430.00–438.99), given the focus of our analysis on instantaneous-to-short-run smoke effects.

[7] Particulate Matter (PM) is a mixture of small particles and liquid droplets. They can be emitted from automobiles, industry, power plants, or fires. Particles smaller than 10 $\mu g/m^3$ can affect heart and lungs and lead to serious health effects. Fine particles of 2.5 $\mu g/m^3$ or less pose the largest threat. They are the “signature pollutants” generated by forest fires (U.S. Environmental Protection Agency, 2011b).

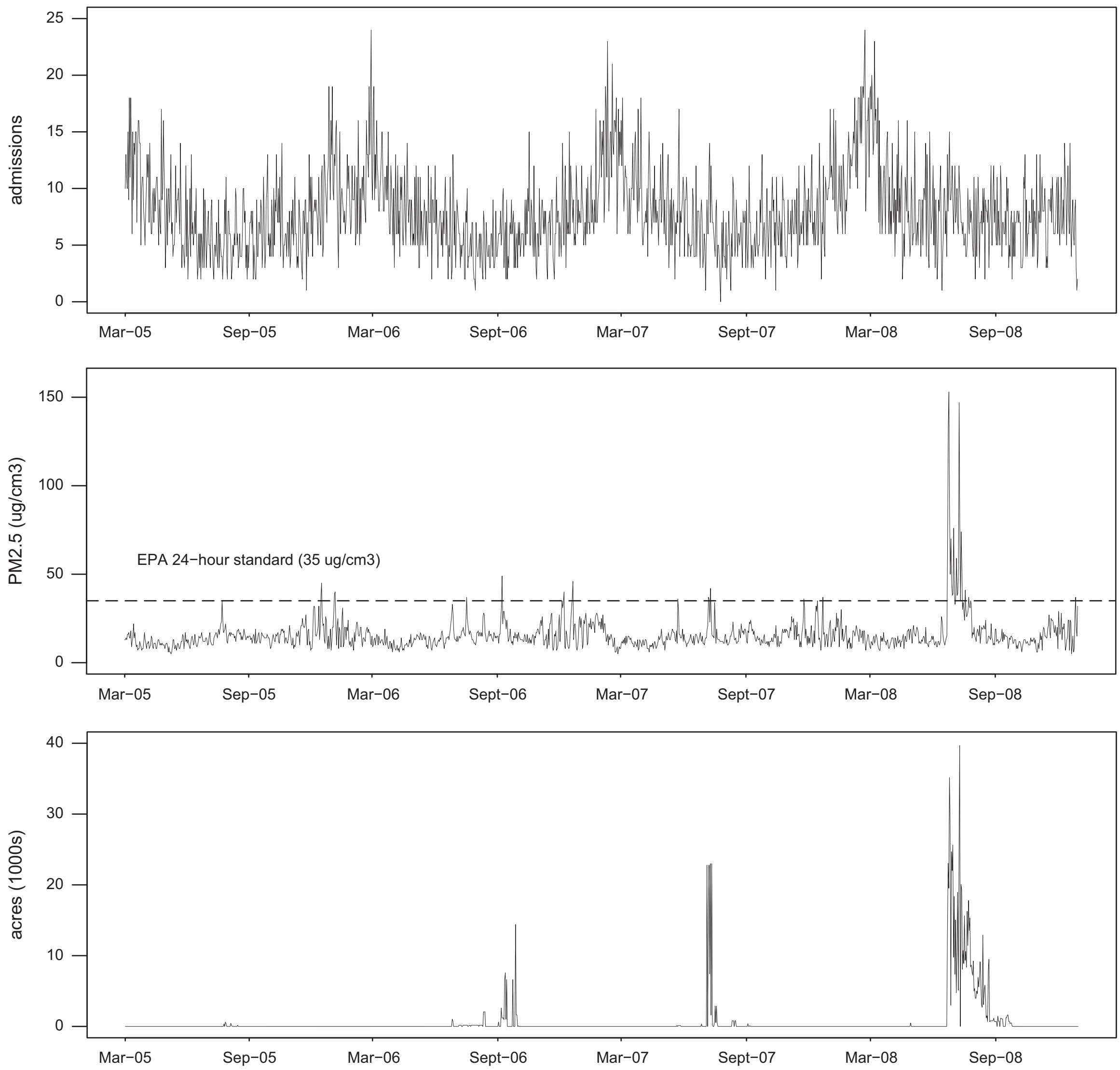


**Fig. 3.** Respiratory admissions, $PM_{2.5}$, and acres burned, 2005–2008.

The Nevada Center for Health Statistics and Informatics also made available summary statistics of treatment costs for our targeted time period and illness codes.

Each inpatient receives a *primary* ICD code upon admission. This guards against any double-counting of respiratory and cardiovascular incidents for the same patient and visit. Health cost figures are also based on this primary admission code. Inpatient admissions originate either at the hospital's Emergency Room (ER), or constitute urgent transferrals from another health care provider such as a doctor's office.[8]

As noted in Kochi et al. (2010) the effect of air pollution can vary greatly over demographic segments. Specifically, the very young and the elderly may be especially vulnerable to wildfire smoke. We therefore assign special attention to the age groups of “under five” and “over 65”. Table 2 displays admission counts and treatment costs for both disease categories, for the three resulting population segments and the overall sample. Overall, 10,318 patients were admitted for acute respiratory syndrome over our research period. This translates into an average daily count of 7.38, with a standard deviation of 3.62. The sample average for treatment costs, in 2008 dollars and averaged over annual figures, amounts to $35,385, with a standard deviation of $53,000 and a median of $19,870. Admission counts are highest for the over-65 population segment,

[8] To be captured in our data, a patient had to spend at least one night at the hospital. It would be desirable to also include emergency room (ER) visits and urgent doctor referrals that did not require an overnight stay in our patient counts. However, this information was not available for our research area during the time frame under consideration. As such, our cost estimates must be interpreted as lower bound for all urgent care visits related to respiratory or cardiovascular problems. This is discussed further in the concluding section.

**Table 2**
Patient counts and treatment costs.

| Age group | Admission counts | | | | Treatment cost (2008 dollars) | | |
|---|---|---|---|---|---|---|---|
| | Total | Daily | | | | | |
| | | Mean | Std | Median | Mean | Std | Median |
| *Respiratory illness* | | | | | | | |
| Under 5 | 1061 | 0.76 | 1.06 | 0 | 13,611 | 19,252 | 8979 |
| 5–65 | 4163 | 2.98 | 1.89 | 3 | 38,337 | 60,605 | 19,432 |
| Over 65 | 5094 | 3.64 | 2.23 | 3 | 37,508 | 49,321 | 23,081 |
| All | 10,318 | 7.38 | 3.62 | 7 | 35,385 | 53,004 | 19,870 |
| *Cardiovascular illness* | | | | | | | |
| Under 5 | 3 | 0.00 | 0.05 | 0 | 22,656 | 19,539 | 13,160 |
| 5–65 | 1943 | 1.39 | 1.18 | 1 | 53,566 | 54,784 | 40,625 |
| Over 65 | 2999 | 2.14 | 1.55 | 2 | 43,783 | 46,773 | 29,471 |
| All | 4945 | 3.53 | 1.96 | 3 | 47,614 | 50,375 | 32,795 |

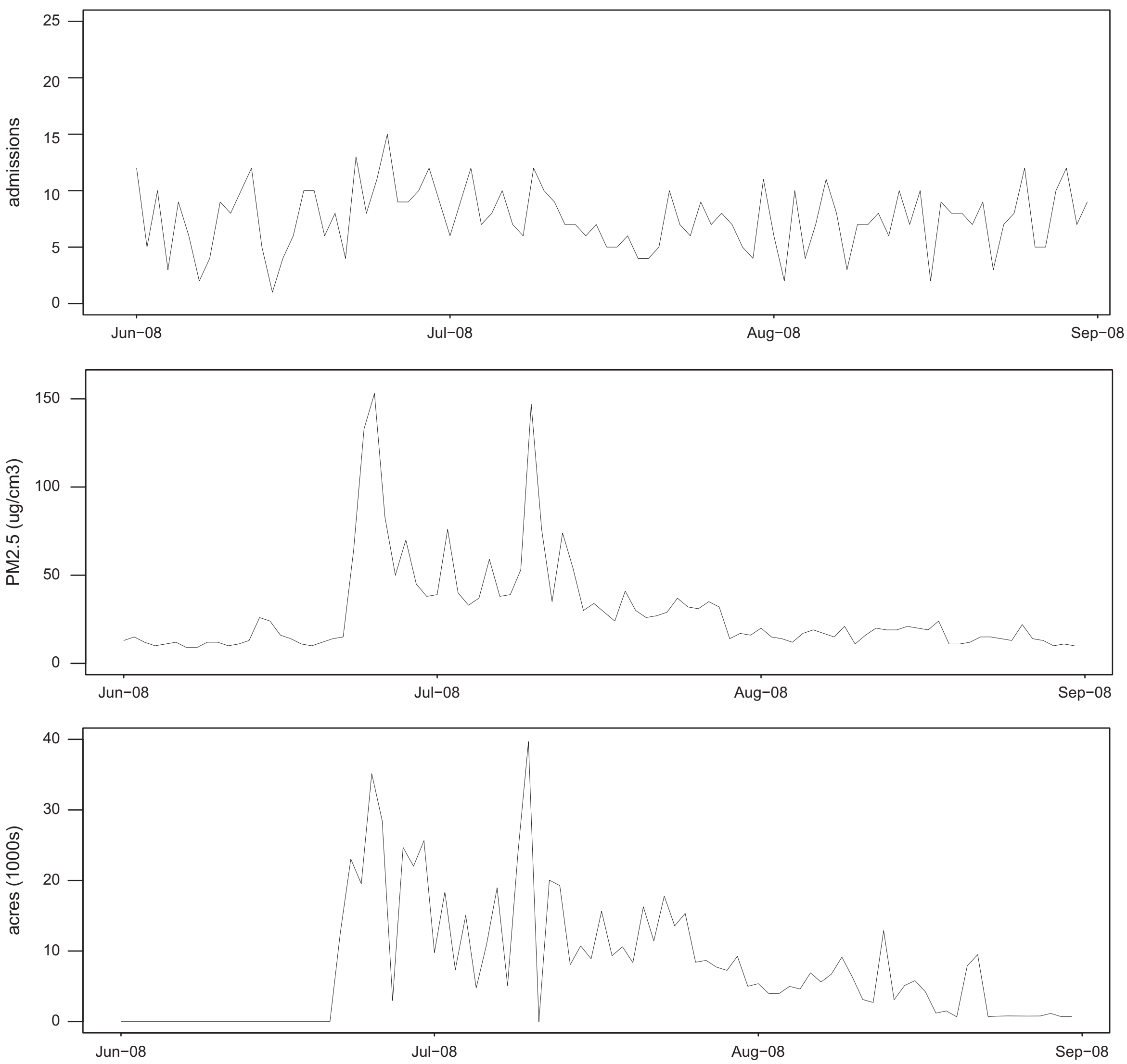


**Fig. 4.** Admissions, $PM_{2.5}$, and acres burned, summer 2008.

and lowest for the under-5 group. Average treatment costs are approximately three times higher for adult patients compared to the youngest segment.

As is evident from the second panel of the table, a total of 4945 patients were admitted for cardiovascular disease, for a daily mean of 3.53 incidents. The bulk of these visits (2999) are associated with patients over 65 years of age. The number of cases involving infants (3) is negligible. Treatment costs for this disease category are approximately 20–40% higher than for respiratory illness, with the highest average cost and cost variability corresponding to the 5–65 segments.

The entire time series of daily admissions for respiratory illness is plotted in the top panel of Fig. 3. The graph shows a clear seasonal pattern with peaks in late winter/early spring and troughs in late summer/early fall. The peaks likely reflect the poorer air quality during the winter season, perhaps combined with the onset of spring allergies. Comparing the top with the center panel, there seems to be a mild correlation of admissions with winter peaks of $PM_{2.5}$. Contemporaneous patterns with acres burned and resulting non-winter peaks of $PM_{2.5}$ are less obvious at this multi-year scale. However, when zooming in on a narrower time frame closer correlation patterns can be discerned. This is shown in Fig. 4, which focuses on the 2008 fire season. Acres burned and $PM_{2.5}$ are well-synchronized, and patient counts also appear reactive to fires, at least during the most intense burn period.

Figs. B1 and B2 in Appendix B show the same triplets of graphs with respect to cardiovascular admissions. While the general time series pattern is somewhat more erratic than for respiratory admissions, there appear to be recurring peaks during mid-summer and mid-winter, i.e. during periods of more extreme weather. As indicated by Fig. B2, which focuses on the 2008 wildfire season, cardiovascular admission counts' reactiveness to wildfire activity and $PM_{2.5}$ levels is somewhat more difficult to establish based on a purely graphical inspection. While patient counts seem to be reactive to extreme $PM_{2.5}$ peaks, counts are equally high or higher in the weeks preceding and following the peak wildfire season. Overall, however, these graphical explorations provide sufficient evidence of an interplay between wildfire events, $PM_{2.5}$ levels, and patient counts for both disease groups to warrant a more rigorous econometric analysis.

## Econometric framework

### *Identification*

In the first stage of our analysis we wish to relate daily $PM_{2.5}$ levels at the impact area to current and lagged daily *effective acres* burned by active fires. In addition, we aim at further differentiating these marginal per-acre effects by fire distance and fuel type. To allow for potentially nonlinear effects of distance on $PM_{2.5}$ contribution, we specify a tractable number of *distance zones* within which we assume marginal effects are constant. However, per-acre $PM_{2.5}$ impact is allowed to vary across these zones.

The choice of appropriate distance zones and permissible RDIR deviations (parameter $d$ above) is related, as a tighter deviation criterion reduces the number of effective fire days and burned acres at any distance. If, in addition, distance zones are defined too tightly, there may not be enough effective fire days left within a given zone to identify corresponding marginal effects. This is illustrated in Appendix A, Table A2. The table lists fire statistics by distance zones in 50-mile increments, for each of four deviation criteria, i.e. $d \in \{30, 60, 90, 120\}$. For example, using a $R_t \pm 30$ criterion would eliminate all effective acres beyond 250 miles (top panel). At $R_t \pm 60$ only four fires contributing a total of 11 effective days would be captured for the $>250$ miles zone.

The combination of distance zones and deviation criteria also affects the ability to identify fuel effects. For example, there are no high fuel burns within the nearest 50 miles at any setting of $d$. At settings of $d=30$ or $d=60$ all low fuel fires are eliminated for distance zone 51–100 miles. Furthermore, fires beyond 300 miles are located exclusively in high-fuel ecosystems.

On the other hand, setting a nearest perimeter of 50 miles is meaningful from a geographic and ecological perspective, as this circle is entirely located in the eastern foothills of the Sierra Nevada and comprises a homogeneous vegetation cover of sagebrush and juniper. In addition, smoke from these nearby fires does not need to be carried across the crest of the Sierra mountains, and can thus be easily transported to the impact area at even light to moderate wind speeds. Similarly, most fires in the 51–100 mile zone occur on the fuel-rich but moist western slopes of the Sierras (see Fig. 2). Compared to more distant high-fuel fires in drier environments, fires along these western slopes likely burn with lower *intensity*, with correspondingly lower smoke production.[9]

Given these considerations and the related identification issue of concurrent fires discussed below, we settle for a four-tiered segmentation based on distance: 0–50 miles (zone 1), 51–100 miles (zone 2), 101–200 miles (zone 3), and $>200$ miles (zone 4). Based on intuition and an econometric specification search (discussed below in more detail) we also vary the RDIR deviation setting across these zones, with a relatively more lenient setting of $d=90$ for zones 3 and 4, a somewhat more stringent setting of $d=60$ for zone 2, and a tight setting of $d=30$ for the nearest perimeter. This is based on the intuition that more remote fires need longer time to send smoke to the impact area. This exposes the plume to more hourly

[9] Fire intensity is primarily assessed by flame length. A high intensity fire reaches up to the tree canopy, resulting in what is commonly known as a "crown fire". Unfortunately, the sparse information on fire intensity available from official sources proved too fragmented and temporarily and spatially coarse to be of any practical use for this study.

**Table 3**
Effective burn days and acres.

| Zone | Distance (miles) | RDIR deviation (deg) | Effective fires | | | Acres burned | |
|---|---|---|---|---|---|---|---|
| | | | Count | Days | % High fuel | Total | % High fuel |
| 1 | 0–50 | 30 | 4 | 8 | 0 | 3670 | 0 |
| 2 | 51–100 | 60 | 7 | 59 | 100 | 215,660 | 100 |
| 3 | 101–200 | 90 | 6 | 99 | 50 | 266,976 | 64 |
| 4 | > 200 | 90 | 7 | 129 | 57 | 404,904 | 56 |
| All | | | 24 | 295 | 62 | 891,210 | 69 |

variability in wind patterns, calling for a more relaxed RDIR deviation. Other than allowing for a sufficient number of effective fire days for identification purpose, this strikes us as a reasonable compromise between "false positives" (counting fire days that should not be included) and "false negatives" (omitting days that, in fact, did send smoke to the target zone).

Table 3 summarizes the resulting statistics for effective fires. Each distance zone comprises between four and seven effective fire events, contributing between eight (zone 1) and 129 (zone 4) active fire days. As mentioned above, zone 1 only includes low fuel fires, while zone 2 comprises exclusively high-fuel events. Thus, identification of marginal fire effects by fuel type is restricted to the more distant zones 3 and 4, which exhibit a relatively even distribution across the two fuel types.

The distinction of marginal effects by distance and fuel type poses an additional identification problem on days where multiple fires of different fuel types and/or distance zones contribute effective acres, since it is only the combined smoke impact from all concurrent fires that can be measured at the target area. Conversely put, the daily contribution of an individual burn (or contemporaneous fires of the same distance zone/fuel type combination) is only identified if no other fire (or fires of a different distance zone/fuel type combination) adds effective acres to the smoke mix that day. In other words, a fire is *temporally* identified if no other burn event is active that day within the 500 mile perimeter of Reno/Sparks. Alternatively, a fire is *spatially* identified if on that day no other fire contributes *effective acres* to the smoke mix. This can occur when concurrent fires are geographically dispersed in a way such that the resultant wind direction for that day, plus/minus our deviation tolerance, "picks up" smoke only from one specific burn (or multiple burns belonging to the same distance and fuel type).

Table A3 in Appendix A depicts the fully identified effective fire days for each distance zone, fuel type, and deviation criterion. At our preferred setting of $d=30$ for zone 1 four days in our data are uniquely identified to contribute low fuel smoke to the $PM_{2.5}$ mix in Reno/Sparks. For zone 2 12 effective days are identified for high-fuel fires at our preferred setting of $d=60$. At $d=90$, the identified number of effective days for zone 3 are 5 for low fuel fires and 11 for high fuel events. The corresponding values for zone 4 are 13 and 18, respectively.

While these numbers of uniquely identified, distance and fuel-specific effective fire days are somewhat lower than would ideal, they still allow for meaningful inference on marginal effects for most distance zones, as shown below. Capturing more identified days by boosting the deviation tolerance (say to $d=120$ for all zones) collects too many "false positive" days and produces counter-intuitive marginal effects. More details on our specification search with respect to optimal settings of $d$ over distance zones are available in the journal's online repository of supplemental material (henceforth referred to as "online appendix"), which can be accessed via www.aere.org/journals.

Our decision rule for the identification of effective fire days based on deviation criteria for each distance zone carries over for lagged effects: For a given daily acreage consumed to have a legitimate effect on $PM_{2.5}$ for the following day, the fire location has to fall within $R_t \pm d^\circ$ for two consecutive days. An effective impact two days into the future requires satisfying the $R_t \pm d^\circ$ for three days in a row, and so on, where $d$ remains constant within each distance zone.

## $PM_{2.5}$ model specification

Our first-stage model relates daily $PM_{2.5}$ measurements to wildfire activity and a set of control variables. Specification tests based on preliminary regression runs clearly indicate the presence of first-order autocorrelation. We thus employ an auto-regressive distributed lag (ARDL) regression model with the dependent variable given as daily $PM_{2.5}$ in micro-grams per cubic meter.[10] Formally, the model can be stated as

$$\begin{aligned} y_t &= \mathbf{x}_f'\boldsymbol{\beta}+\mathbf{x}_m'\gamma+\mathbf{x}_t'\boldsymbol{\delta}+\varepsilon_t, \quad \text{with} \\ \varepsilon_t &= \rho\varepsilon_{t-1}+\mu_t, \quad \text{where} \quad \mu_t \sim n(0,\sigma^2) \end{aligned} \tag{1}$$

The first set of regressors, $\mathbf{x}_f$, includes effective acres burned for each of the four distance zones mentioned above. For zones 3 and 4, this vector further distinguishes between acres burned in low and high fuel environments, respectively.

[10] Using $PM_{2.5}$ in log form does not improve model fit and complicates the interpretation of marginal effects, especially when combined with the patients model below. We thus prefer this simple linear specification.

Vector $\mathbf{x}_f$ also includes lagged effects for each distance zone and, where applicable, fuel type. Considering typical sustained wind speeds of 10–20 mph in the Sierras and eastern foothills, we assume that smoke from a given burn zone, if carried in the right direction, should reach the impact area within a maximum of 3 days for even the most remote fires in our set. Furthermore, after a few days large-scale smoke dispersion is likely to preempt any association with underlying consumed acres (Lipsett et al., 2008). We thus ex ante allow for up to three lags for these fuel/distance interactions.

An econometric specification search further refined this starter setting to up to two lags for zones 2–4, and only concurrent fire days for zone 1. Details for this search, which comprises 16 different models varying in included lags and RDIR deviations per lag and distance zones are given in the online Appendix. The basic considerations underlying this search are listed in Appendix C.

The second set of covariates in Eq. (1), denoted as $\mathbf{x}_m$, captures daily meteorological statistics for the Reno/Sparks area. These include average temperature (`avgtemp`), mean daily dew point (`dewp`), average and maximum sustained wind speed (`avgwind, maxwind`), precipitation (`prcp`), minimum and maximum relative humidity (`mnrh, mxrh`), and average daily air pressure (`pres`).

The final vector of explanatory variables, labeled $\mathbf{x}_t$ in (1), collects monthly indicator terms, with January as the baseline period, as well as day-of-week indicators, with “Sunday” as base category. This controls, respectively, for seasonal variation in $PM_{2.5}$, such as increased levels due to inversion conditions and wood burning in winter, and weekday-based differences in traffic volume and wood burning.[11] The model is completed by three corresponding sets of coefficients, $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$ and $\boldsymbol{\delta}$, and an autoregressive normal error term with first-order autocorrelation parameter $\rho$. For ease of exposition, all acres-burned measures are scaled to units of 100 in our empirical model.

### *Patients model*

We follow existing contributions to the air pollution/health outcome literature (e.g. Smith et al., 2000; Clyde, 2000) and model the effect of $PM_{2.5}$ on the daily number of hospital admissions within a count data regression framework. We ex ante consider several candidate specifications, including a standard Poisson model, a Poisson model allowing for over-or under-dispersion (labeled the *Poisson GLM* model in Wooldridge, 2012, section 18.2), a fully robust Poisson model with respect to any variance mis-specification (estimated via Quasi-Maximum Likelihood (QMLE)), and two Negative-Binomial count models, i.e. the *NEGBIN I* and *NEGBIN II* specifications as given in Cameron and Trivedi (1986). The detailed results for each of these models are available in the online Appendix.[12]

Both NEGBIN models and the Poisson GLM point at very mild overdispersion, with the GLM variance scalar amounting to 1.12, and the NEGBIN parameters being estimated in the 0.01–0.09 range (a value of zero would indicate no over-dispersion). Since it is difficult to further distinguish between these three closely related models we opt for the fully robust Poisson QMLE approach as our preferred specification for the patient models. As is well known, this approach produces consistent coefficient estimates under any variance mis-specification, as long as the conditional mean function is correctly specified (e.g. Gourieroux et al., 1984). Detailed expressions for the robust estimator of the variance–covariance matrix for the coefficient vector are given in Gourieroux et al. (1984) and Wooldridge (2012, section 18.2.3).

Using the standard exponential parameterization of the Poisson expectation we thus obtain

$$
\begin{aligned}
&f(y_t|\lambda_t) = \frac{\exp(-\lambda_t)\lambda_t^{y_t}}{y_t!}, \quad \text{where}\\
&\quad E(y_t) = V(y_t) = \lambda_t, \quad \text{and}\\
&\quad \lambda_t = \exp(\mathbf{z}_p'\boldsymbol{\beta} + \mathbf{z}_m'\boldsymbol{\gamma} + \mathbf{z}_t'\boldsymbol{\delta})
\end{aligned}
\tag{2}
$$

We estimate separate Poisson models for respiratory and cardiovascular patients. In each case the parameterized mean function $\lambda_t$ includes three sets of regressors: $\mathbf{z}_p$, a vector of air pollutant measures, meteorological indicators $\mathbf{z}_m$, and temporal indicators $\mathbf{z}_t$. Pollutants include $PM_{2.5}$, carbon monoxide, and ozone. The second is another signature ingredient of biomass smoke (e.g. Fowler, 2003), and the third is a known irritant that can trigger respiratory ailments (Yang et al., 1997, 1998; U.S. Environmental Protection Agency, 2011a). The vector of meteorological variables is identical to $\mathbf{x}_m$ in the $PM_{2.5}$ model, with the addition of daily minimum and maximum temperature (`mintemp, maxtemp`). As before, the temporal variables in $\mathbf{z}_t$ include indicators for calendar months (baseline=January) and day-of-week (baseline=Sunday).[13] For both

[11] Adding year-specific fixed effects to this temporal indicators had no measurable impact on results.

[12] Based on the suggestion of a reviewer, we test for potential endogeneity of $PM_{2.5}$ using the residuals from the first-stage model following Wooldridge (2012, section 18.5). This endogeneity test proves insignificant for all our specifications (respiratory/cardio, and various age groups), suggesting that there are no endogeneity problems with $PM_{2.5}$ in the patients models. For completeness, we also estimate an Instrumental Variables (IV) version of the Poisson model following Mullahy (1997). As expected, this leads to efficiency losses, pushing the level of significance of $PM_{2.5}$ in the respiratory model above 5%. The details of these additional robustness checks are given in the online Appendix.

[13] We did not find any significant lagged effects for either pollutants or meteorological indicators on patient counts for either the respiratory illness or the cardiovascular disease model. This contrasts with Viswanathan et al. (2006) who report a 1–1.5 day lag between elevated $PM_{2.5}$ levels and asthma admissions for the 2003 San Diego fires. Acute respiratory and cardiovascular impacts thus appear to be more immediate for our study area. It is also possible that easier and/or lower-cost hospital access may have prompted patients to seek medical help faster than for the San Diego case. This is an interesting question for future research.

disease categories we estimate separate admission count models for the entire sample, and the sub-populations of “under five” and “over 64”.

## Estimation results

### $PM_{2.5}$ model

We estimate the $PM_{2.5}$ model via Full-Information-Maximum-Likelihood (FIML), which produces estimates of all slope coefficients, along with the error correlation coefficient $\rho$ and the variance of the *i.i.d.* stochastic component, $\sigma^2$. The results from this model are shown in Table 4. The left half of the table gives coefficient estimates for acres burned within each distance/fuel category, sorted by zone and fuel intensity. Each current marginal effect is followed by its first and second-order lagged counterparts, as applicable. Results for meteorological covariates and temporal fixed effects are given in the right half of the table.[14]

As can be seen from the table, the marginal effect for the nearest zone has the expected sign, but falls slightly below the 10% level of significance. The number of identified effective fire days (see above) is simply too small to allow for a more precise estimation of this effect. In contrast each of the remaining distance/fuel combination produces at least one highly significant coefficient estimate. Specifically, eight of the 10 lagged effects are estimated at 5% significance or higher. This highlights the importance of allowing for smoke travel time. In general, these delayed effects taper off with higher lags, as expected. By model construction (see Appendix C and online Appendix) the cumulative marginal effect over all lags is higher for high-fuel fires compared to low-fuel burns within zones 3 and 4. In addition (and *not* by construction) both fuel effects are relatively lower for the most remote zone compared to the 101–200 mile perimeter.

Of the remaining regressors we note the expected significant and negative effect of local wind speed (`avgwind`, `maxwind`) and the negative differential effect of month indicators compared to the January baseline. In contrast, our day-of-week indicators do not contribute exacting strength to the model.

Table 5 shows the cumulative marginal effect for each distance/fuel category, computed as linear combination of all significant current and lagged effects from Table 4 (see e.g. Koop and Tole, 2004), with corresponding standard errors and confidence intervals. As mentioned above, these effects are internally consistent across fuel types for the two outer zones, and diminish going from zone 3 to zone 4, as expected.

The only counter-intuitive result is the relatively low marginal effect for the high-fuel fires included in the 51–100 mile perimeter, compared to high-fuel effects for more remote zones. This is likely related to the higher fuel moisture and corresponding lower *burn intensity* for this zone, as mentioned earlier. In addition, all fires in zone 2 are located immediately across the spine of the Sierra Nevada mountain range. Smoke from these burns has to rise quickly and highly, then drop rather abruptly to reach the target zone. This may be difficult to achieve given prevailing wind patterns.

In general, however, the patterns of marginal effects captured in Table 5 appear reasonable. We conclude that an additional 100 acres consumed, controlling for feasibility of wind transport via our $R_t \pm d$ method, increases local $PM_{2.5}$ levels by 0.1–0.3 $\mu g/m^3$, depending on distance, fuel type, and, possibly, fire intensity. Furthermore, this effect does not diminish rapidly over fire distance. Even fires as remote as 200–300 miles can contribute to significantly elevated $PM_{2.5}$ levels.

### Patients model

As discussed above the patients model is estimated via Quasi-Maximum Likelihood (QMLE), which generates fully robust standard errors for the coefficients in the parameterized mean function. Estimation results for this model for all respiratory inpatients, and the sub-groups of “under five” and “over 65” are captured in Table 6. The key finding from this analysis is the significant effect of $PM_{2.5}$ for the “all patients” case. As shown in the first block of results of the table, the full-sample model estimates an increase in expected respiratory admissions by 0.3% due to a 1 $\mu g/m^3$ increase in $PM_{2.5}$ concentration.[15] In contrast, we do not detect a significant effect of $PM_{2.5}$ for the very young and very old patients. Thus, the link between particulate matter and hospitalization rates for our sample is largely identified by the 5–65 population segment.[16]

The other two included pollutants, `co` and `ozone`, are not associated with significant effects on admission counts (at 5% or higher) for any of the population categories. Of the meteorological covariates, higher air pressure reduces patient

[14] We also estimate models based on, respectively, distance category and fuel types alone. These specifications are rejected at any level of significance using likelihood-ratio tests. Furthermore, we estimate our preferred specification with carbon monoxide and, respectively, ozone as dependent variables. We do not find any significant wildfire effects of any appreciable magnitude for these two pollutants. The detailed results of these CO and $O^3$ models are provided in the online Appendix.

[15] Given the exponential parameterization of the mean function, the estimated coefficients reflect fractional changes. Multiplying by 100 yields percentage figures.

[16] The lack of significant pollution effects on admissions related to respiratory illness for the very young and elderly might be related to insurance coverage. Reno/Sparks has a large population of transient workers affiliated with the Casino industry. Many of them might have no or insufficient health coverage, especially for dependents. If dependents (young, elderly) are less likely to be covered than the working population, they may be more reluctant to seek professional treatment for respiratory problems. In contrast, cardio-vascular attacks are likely life-threatening, such that treatment is sought irrespective of insurance coverage.

**Table 4**
Estimation results for the $PM_{2.5}$ model.

| Variable | Coeff. | (s.e.) | Variable | Coeff. | (s.e.) |
|---|---|---|---|---|---|
| 0–50 miles | | | | | |
| lowfuel | 0.273 | (0.181) | avgtemp | 0.051 | (0.054) |
| | | | dewp | −0.028 | (0.058) |
| 51–100 miles | | | avgwind | −0.512 | (0.096)*** |
| highfuel | 0.005 | (0.012) | maxwind | −0.109 | (0.049)** |
| highfuel.L1 | 0.098 | (0.008)*** | prcp | −5.159 | (2.738)* |
| highfuel.L2 | 0.043 | (0.010)*** | mnrh | −0.012 | (0.025) |
| | | | mxrh | 0.049 | (0.025)** |
| 101–200 miles | | | pres | −2.012 | (1.993) |
| lowfuel | 0.029 | (0.020) | | | |
| lowfuel.L1 | 0.173 | (0.020)*** | feb | −4.139 | (2.198)* |
| lowfuel.L2 | 0.062 | (0.032)** | mar | −5.734 | (2.435)** |
| | | | apr | −5.364 | (2.437)** |
| highfuel | 0.114 | (0.013)*** | may | −4.667 | (2.398)* |
| highfuel.L1 | 0.085 | (0.011)*** | jun | −3.254 | (2.373) |
| highfuel.L2 | 0.112 | (0.017)*** | jul | −2.018 | (2.415) |
| | | | aug | −4.092 | (2.607) |
| > 200 miles | | | sep | −4.443 | (2.163)** |
| lowfuel | −0.016 | (0.019) | oct | −5.006 | (2.482)** |
| lowfuel.L1 | 0.080 | (0.019)*** | nov | −2.940 | (1.943) |
| lowfuel.L2 | 0.024 | (0.030) | dec | −0.044 | (1.563) |
| | | | mon | 0.290 | (0.550) |
| highfuel | 0.172 | (0.007)*** | tue | 0.925 | (0.619) |
| highfuel.L1 | 0.063 | (0.011)*** | wed | 0.950 | (0.672) |
| highfuel.L2 | 0.011 | (0.011) | thr | 0.669 | (0.689) |
| | | | fri | 0.673 | (0.632) |
| $\rho$ | 0.565 | (0.011)*** | sat | 0.550 | (0.511) |
| $\sigma$ | 5.281 | (0.046)*** | constant | 68.645 | (51.868) |

*** Significance levels: 1%.
** Significance levels: 5%.
* Significance levels: 10%.

**Table 5**
Marginal effects for the $PM_{2.5}$ model (μg/m$^3$ per 100 acres burned).

| Distance zone / fuel type | Estimate | (s.e.) | Lower | Upper |
|---|---|---|---|---|
| 51–100 miles | | | | |
| High fuel | 0.141 | (0.013) | 0.115 | 0.166 |
| 101–200 miles | | | | |
| Low fuel | 0.235 | (0.045) | 0.147 | 0.324 |
| High fuel | 0.310 | (0.017) | 0.276 | 0.344 |
| > 200 miles | | | | |
| Low fuel | 0.080 | (0.019) | 0.043 | 0.116 |
| High fuel | 0.235 | (0.012) | 0.212 | 0.258 |

Lower/upper, bounds for 95% confidence interval.

counts for the full-sample model, as does increased precipitation for the “over 65” case. The latter is intuitively sound as precipitation has the ability to wash particulates out of the air, while the former is somewhat counter-intuitive. High pressure generally prevents the mixing of air layers and can promote inversion during the cold season. It is possible that some residents avoid outdoor activities on high pressure days with obviously poor air quality (especially during the winter), thus reducing the probability of respiratory problems. Another explanation might be that Reno residents travel to the nearby mountains for recreational activities on nice (high-pressure) days, avoiding polluted air along the valley floor.

In addition, we find an – expected – significant negative weekend effect for the full sample (which includes all of the working residents). The month indicators reflect the pattern from Fig. 3: patient admissions are highest in February/March, and lowest in July–September, ceteris paribus.[17]

[17] Following a referee's suggestion, we also estimate these models focusing exclusively on patients whose visit to the hospital originated in the Emergency Room (ER). This reduces our sample by approximately 20% for all age groups. The results remain virtually unchanged compared to the full-sample model. In addition, we estimate the patients model focusing exclusively on asthma cases (ICD codes 493.00–493.99, 999 cases in total), which constitutes a sub-sample of all respiratory patients. We find a significant $PM_{2.5}$ effect that is three times stronger than for the general model. This stresses the increased vulnerability of asthma-susceptible residents to elevated $PM_{2.5}$ levels. Furthermore, we estimate a “placebo” model using incidents of cancer

**Table 6**
Results for the respiratory admissions model.

| Variable | All patients | | Under 5 | | Over 65 | |
|---|---|---|---|---|---|---|
| | Coeff. | (s.e.) | Coeff. | (s.e.) | Coeff. | (s.e.) |
| $PM_{2.5}$ | 0.003 | (0.001)** | 0.003 | (0.008) | 0.001 | (0.002) |
| CO | 0.041 | (0.080) | −0.498 | (0.278)* | 0.184 | (0.113) |
| Ozone | −2.684 | (2.301) | −4.277 | (6.929) | −0.047 | (3.179) |
| avgtemp | 0.008 | (0.006) | 0.029 | (0.016)* | 0.010 | (0.008) |
| dewp | −0.004 | (0.003) | 0.002 | (0.010) | −0.004 | (0.005) |
| avgwind | −0.002 | (0.007) | −0.008 | (0.019) | −0.003 | (0.010) |
| maxwind | 0.004 | (0.003) | 0.010 | (0.009) | 0.003 | (0.004) |
| maxtemp | −0.003 | (0.004) | −0.008 | (0.010) | 0.000 | (0.005) |
| mintemp | −0.001 | (0.004) | −0.018 | (0.010)* | −0.006 | (0.005) |
| prcp | 0.095 | (0.122) | −0.248 | (0.395) | 0.322 | (0.129)** |
| mnrh | 0.002 | (0.002) | 0.002 | (0.004) | 0.003 | (0.002) |
| mxrh | 0.001 | (0.002) | 0.004 | (0.005) | 0.000 | (0.002) |
| pres | −0.216 | (0.100)** | 0.129 | (0.278) | −0.123 | (0.132) |
| feb | 0.355 | (0.051)*** | 0.432 | (0.139)*** | 0.387 | (0.072)*** |
| mar | 0.278 | (0.056)*** | 0.182 | (0.171) | 0.320 | (0.080)*** |
| apr | −0.056 | (0.063) | −0.555 | (0.207)*** | 0.021 | (0.090) |
| may | −0.189 | (0.074)** | −1.037 | (0.249)*** | −0.047 | (0.102) |
| jun | −0.359 | (0.089)*** | −1.328 | (0.315)*** | −0.210 | (0.122)* |
| jul | −0.578 | (0.099)*** | −1.719 | (0.359)*** | −0.478 | (0.140)*** |
| aug | −0.515 | (0.096)*** | −1.763 | (0.333)*** | −0.425 | (0.131)*** |
| sep | −0.421 | (0.084)*** | −1.623 | (0.295)*** | −0.314 | (0.114)*** |
| oct | −0.294 | (0.066)*** | −1.139 | (0.224)*** | −0.269 | (0.095)*** |
| nov | −0.300 | (0.056)*** | −1.157 | (0.184)*** | −0.209 | (0.080)** |
| dec | −0.156 | (0.047)*** | −0.721 | (0.152)*** | −0.125 | (0.069)* |
| mon | 0.113 | (0.041)*** | 0.191 | (0.133) | 0.127 | (0.056)** |
| tue | 0.162 | (0.039)*** | 0.313 | (0.120)** | 0.196 | (0.055)*** |
| wed | 0.160 | (0.042)*** | 0.290 | (0.120)** | 0.185 | (0.059)*** |
| thr | 0.114 | (0.039)*** | 0.181 | (0.127) | 0.173 | (0.054)*** |
| fri | 0.141 | (0.042)*** | 0.153 | (0.123) | 0.204 | (0.057)*** |
| sat | 0.022 | (0.041) | 0.003 | (0.125) | 0.046 | (0.056) |
| constant | 7.387 | (2.630)*** | −3.479 | (7.313) | 3.980 | (3.497) |

*** Significance levels: 1%.
** Significance levels: 5%.
* Significance levels: 10%.

Results for the cardiovascular patients model are captured in Table 7. There are not enough observed cases for the "under five" population segment to allow for a formal analysis. We therefore restrict our attention to the full model including all patients and the "over 65" segment. As is evident from the table, $PM_{2.5}$ has a significant positive effect for both sub-models. In both cases the marginal effect is stronger than for the respiratory admissions model, amounting to 0.5% for the general population and 0.6% for the elderly. In contrast, climate and month-specific effects do not play a major role in the cardiovascular case. As for respiratory illness, most patient visits occur during the work week.

The cardiovascular models include a regressor that is not present in the respiratory illness specifications: `hiCOdays`. This indicator variable flags days in our series with CO levels in the top 20th percentile (approximately 0.57 ppm). As can be seen from the full model, it has a significant *negative* effect on patient counts. We added this variable after observing a counter-intuitive negative sign for CO in our baseline specification. Additional inspection revealed that this effect is exclusively driven by days with extremely high CO measures, all of which occur in the winter months. On such days, patient counts were relatively lower than expected. This points at averting behavior – some, potentially vulnerable, individuals may choose to avoid exposure on days with obviously poor air quality. Capturing these days explicitly in our model leaves the remaining CO effect insignificant.[18]

(*footnote continued*)
(ICD codes 140.00–208.99) as dependent variable. A significant $PM_{2.5}$ effect in this model would cast doubt on our results for the respiratory and cardiovascular illness applications, suggesting that $PM_{2.5}$ is absorbing some omitted contemporaneous effect across our research period. However, as expected, none of the coefficients associated with pollutants or climate indicators emerge as significant for the cancer specification. The results for all these additional models are available in the online Appendix.

[18] We note that the effect of $PM_{2.5}$, which is central to our analysis, remained robust to this modification. Furthermore, an equivalent indicator for days with extreme $PM_{2.5}$ levels did not emerge as significant in either model (full sample and over 65). We hypothesize that this is largely due to the wildfire effect. While there is considerable overlap between winter days with high CO and $PM_{2.5}$ levels, this is not the case during the wildfire season. It thus appears that vulnerable residents are less likely to avoid exposure to poor air quality in summer compared to winter. This may be due to a higher opportunity cost of avoiding outdoor activities in the summer. While beyond the scope of this study, a closer examination of averting behavior, how it may change over season, and how this affects exposure to various pollutants would be an interesting avenue for future research.

**Table 7**
Results for the cardiovascular admissions model.

| Variable | All patients | | Over 65 | |
|---|---|---|---|---|
| | Coeff. | (s.e.) | Coeff. | (s.e.) |
| $PM_{2.5}$ | 0.005 | (0.001)*** | 0.006 | (0.002)*** |
| CO | −0.086 | (0.138) | −0.214 | (0.166) |
| hiCOday | −0.141 | (0.064)** | −0.114 | (0.083) |
| ozone | −2.933 | (3.032) | −1.534 | (3.919) |
| avgtemp | 0.005 | (0.008) | 0.011 | (0.010) |
| dewp | −0.004 | (0.004) | −0.005 | (0.006) |
| avgwind | 0.005 | (0.010) | 0.002 | (0.013) |
| maxwind | −0.004 | (0.004) | −0.006 | (0.006) |
| maxtemp | 0.001 | (0.005) | −0.003 | (0.007) |
| mintemp | −0.005 | (0.006) | −0.008 | (0.007) |
| prcp | −0.159 | (0.170) | −0.115 | (0.197) |
| mnrh | 0.001 | (0.003) | 0.003 | (0.003) |
| mxrh | 0.000 | (0.002) | 0.000 | (0.003) |
| pres | −0.110 | (0.141) | 0.074 | (0.173) |
| feb | 0.162 | (0.090)* | 0.216 | (0.114)* |
| mar | 0.123 | (0.082) | 0.202 | (0.109)* |
| apr | 0.018 | (0.089) | 0.107 | (0.118) |
| may | 0.022 | (0.103) | 0.092 | (0.133) |
| jun | 0.011 | (0.120) | 0.156 | (0.153) |
| jul | −0.219 | (0.130)* | −0.227 | (0.173) |
| aug | −0.042 | (0.125) | 0.074 | (0.163) |
| sep | 0.046 | (0.110) | 0.138 | (0.150) |
| oct | 0.087 | (0.091) | 0.196 | (0.117)* |
| nov | −0.022 | (0.080) | 0.091 | (0.107) |
| dec | 0.001 | (0.075) | 0.051 | (0.096) |
| mon | 0.222 | (0.058)*** | 0.250 | (0.072)*** |
| tue | 0.301 | (0.055)*** | 0.296 | (0.072)*** |
| wed | 0.261 | (0.055)*** | 0.278 | (0.071)*** |
| thr | 0.290 | (0.057)*** | 0.348 | (0.074)*** |
| fri | 0.247 | (0.056)*** | 0.216 | (0.073)*** |
| sat | 0.032 | (0.058) | −0.020 | (0.078) |
| Constant | 3.862 | (3.691) | −1.274 | (4.546) |

*** Significance levels: 1%.
** Significance levels: 5%.
* Significance levels: 10%.

Our estimated marginal effect of 0.3% increase in admissions due to a unit change in $PM_{2.5}$ for the respiratory model closely matches similar dose–response effects reported in the existing literature. For example, Tham et al. (2009) find a risk ratio[19] for daily respiratory emergency room attendances during the 2003 Australian wildfire season of 1.02–1.03 for a 10-unit increment in $PM_{10}$, measured in $\mu g/m^3$. Assuming linearity over the examined range, this is equivalent to a 0.2–0.3% increase in risk due to a 1-unit change in $PM_{10}$. Using an approximate $PM_{2.5}$ to $PM_{10}$ ratio of 40–50% (see e.g. Velasco et al., 2005), this, in turn, translates into a percentage increase in risk of 0.4–0.6% for a 1-unit change in $PM_{2.5}$. Using similar transformation steps, Emmanuel's (2000) estimate of a 12% increase in outpatient visits for upper respiratory tract illness due to a 100-unit jump in $PM_{10}$ during the 1997 wilfire haze that blanketed Singapore converts to a marginal $PM_{2.5}$ impact of 0.24%. A comparison with dose–response results from general ambient air pollution studies is equally encouraging. For example, Atkinson (2003) examine the effect of air pollution on respiratory hospital admissions in 29 European cities. They find a 1% increase in admissions due to a 10-unit change in $PM_{10}$, which translates into a marginal $PM_{2.5}$ effect of approximately 0.2%.

In contrast, our estimated marginal effect of 0.5% increase in admissions due to a unit change in $PM_{2.5}$ for the full-sample cardiovascular model is somewhat higher than comparable dose–response estimates reported elsewhere. For example, Zanobetti and Schwartz (2003) relate hospital admissions for cardiovascular disease in 14 U.S. cities to a 10-unit increase in $PM_{10}$, and find a resulting 1% increase in admission counts. This is equivalent to a marginal $PM_{2.5}$ effect of 0.2%. Similarly, Le Tertre et al. (2003) consider hospital admissions for heart disease in reaction to $PM_{10}$ levels in eight European cities. Their estimated effect of 0.5% for a 10-unit change in $PM_{10}$ implies a marginal $PM_{2.5}$ effect of 0.1%. Naturally, the usual caveats of differences in population, definition of illness, time horizon, units of observation, and estimation method apply when

[19] The risk ratio or "Relative Risk" (RR) is a common metric used in the health literature to quantify the impact of pollution on morbidity and mortality. It is defined as the ratio of the probability of experiencing a specific disease for an exposed population relative to that of an un-exposed control group.

comparing these estimates to ours. Nonetheless, it is reassuring that our estimated marginal impacts are clearly in the same "ballpark" of magnitude as those produced by a variety of other studies.

*Marginal fire effects on patient admissions and treatment costs*

So far our estimation results suggest a clear link between fire events and $PM_{2.5}$ concentration in the impact area, as well as a relationship between the latter and patient admission counts for respiratory and cardiovascular illness. We combine these findings and compute a point estimate for the direct effect of acres burned (in units of 100) for a given fuel/distance combination on admissions for each disease category by multiplying the cumulative marginal effect from the $PM_{2.5}$ model (as captured in Table 5) with the marginal $PM_{2.5}$ effect from the corresponding patients model, as shown in Tables 6 and 7.[20]

Standard errors and confidence intervals for these combined effects are derived via simulation. Specifically, we proceed as follows: Using the results from the $PM_{2.5}$ model, we first compute the cumulative marginal effects of Table 5, with corresponding standard errors and confidence intervals (following Koop and Tole, 2004). We then draw a set of 1000 cumulative marginal effects for each distance/fuel combination from their respective asymptotic distribution (i.e. invoking normality). Using the results from the corresponding patients model we take 1000 draws of the marginal effect of $PM_{2.5}$ on expected patient counts from its asymptotic distribution. We then element-by-element multiply the two resulting $1000 \times 1$ vectors of stage one and stage two effects to obtain draws from the asymptotic distribution of the combined effect. The reported standard errors for the combined effect thus reflect the resulting combined asymptotic variability of the stage-specific effects. This variability is then carried forward to all subsequent transformations.[21]

Specifically, multiplying this combined marginal effect by 100 yields the estimated percentage change in patient admissions due to an additional 100 acres consumed by wildfire. Using average patient counts and treatment costs as given in Table 2 above we then translate these percentage changes in admissions into predicted treatment costs. Given the significant and numerically different $PM_{2.5}$ effect for the "over 65" cardiovascular sub-model, we report separate results for this population segment and the full sample in the cardiovascular illness case.

Results are summarized in Table 8. The left half of the table captures the percentage change in admissions, while the right half shows treatment costs in 2008 dollars. For the general population we estimate a 100 acre burn to increase inpatient admissions for acute respiratory syndrome by 0.02 to 0.08%, depending on fuel type and distance zone. This translates into incremental treatment costs of $54 to $209. Percentage changes in admissions are somewhat more pronounced for cardiovascular disease as can be seen from the second block of the table, ranging from 0.4 to 0.15%. Resulting treatment costs range from close to $70 (zone 4, low fuel) to over $250 (zone 3, high fuel). For the elderly segment (third block in the table) increases in admissions and treatment costs are, respectively, 25% and 14% higher than for the general population.

Since each patient admission is uniquely flagged as either respiratory or cardiovascular (based on primary diagnosis, see above), we can add the full-sample costs across the two illness categories. The resulting cost estimates are given in the bottom block of the table. In total, an additional 100 acres of vegetation consumed by wildfire causes smoke-related treatment costs between $121 and $467 for the impact area. Focusing on zones 3 and 4, marginal costs generated by high fuel burns exceed their low fuel equivalents by factors of 1.3 and 2.9, respectively. Interestingly, low fuel costs for zone 3 and high fuel costs for zone 4 are of comparable magnitude.

These figures can add up to substantial amounts in an intense fire season, such as 2008. Multiplying each marginal treatment cost by the total effective acreage consumed in each distance and fuel group that year yields a total cost estimate, across both disease groups, of close to $2.2 million, with 95% confidence bounds of $1.1 million and $3.4 million, respectively.

Treatment costs can also be expressed in terms of individual fire events. For example, consider a typical low-fuel fire in zone 3 with an effective size of 45,000 acres (our sample mean for that category). The expected total treatment costs for our impact area caused by such a burn are $158,000, with bounds of ($72,000, $260,000). In comparison, a high fuel fire of the same size in the same distance zone would push treatment costs to an estimated $210,000, with confident bounds of ($109,000, $318,000).

Our treatment cost estimates lie within the same order of magnitude as those reported in Butry et al. (2001) for the 1998 Florida fires, when translated into a per-100-acre value and expressed in 2008 currency. For their study this yields a figure of

[20] Based on reviewers' suggestions we also experimented with a reduced form approach that directly relates patient counts to the wildfire attributes from the first stage model, in lieu of $PM_{2.5}$. This produced lacking significance and some counter-intuitive signs for some of the fire variables. This is likely due to the fact that this reduced form specification essentially ignores the AR(1) form of the stage-one error term. An alternative would be to explicitly introduce autocorrelation into the reduced-form Poisson model. However, this substantially complicates MLE estimation, relative to our simple and preferred two-model procedure. Additional discussion and detailed results for this reduced-form approach are given in the online Appendix.

[21] Formally, let the cumulative marginal effect of additional acres burned on $PM_{2.5}$, call it $\hat{\beta}_f$ for simplicity, have asymptotic distribution of $\hat{\beta}_f \sim n(\beta_f, V_{\hat{\beta}_f})$ (the standard MLE result), and the marginal effect of $PM_{2.5}$ on expected patient count, call it $\hat{\beta}_p$, have asymptotic distribution of $\hat{\beta}_p \sim n(\beta_p, V_{\hat{\beta}_p})$. Then the estimated combined effect of acres burned on patient counts is $\hat{\beta}_f * \hat{\beta}_p$. This product of normals has a known but rather complex analytical form. However, as illustrated in Ware and Lad (2003, p. 14 and 15), given independence of the two random variables, our simple simulation procedure of drawing $\hat{\beta}_f$ and $\hat{\beta}_p$ from their respective asymptotic distributions, then multiplying each pair of draws, produces draws from this density. We then examine the mean, standard deviation, and 95% confidence bounds of the resulting empirical distribution. In spirit, this approach is also comparable to the "two-step, block-bootstrap procedure" recently employed by Schlenker and Walker (2012) in a similar setting.

**Table 8**
Marginal changes in patient admissions and treatment costs per 100 acres burned.

| Zone | | Admissions (% change in patients) | | | | Treatment cost ($) | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Estimate | (s.e.) | Lower | Upper | Estimate | (s.e.) | Lower | Upper |
| *All respiratory patients* | | | | | | | | | |
| *2* | High fuel | 0.036 | (0.016) | 0.008 | 0.067 | 95 | (41) | 20 | 176 |
| *3* | Low fuel | 0.060 | (0.028) | 0.011 | 0.121 | 157 | (73) | 29 | 317 |
| | High fuel | 0.080 | (0.034) | 0.016 | 0.147 | 209 | (88) | 41 | 383 |
| *4* | Low fuel | 0.021 | (0.010) | 0.003 | 0.044 | 54 | (27) | 9 | 115 |
| | High fuel | 0.061 | (0.025) | 0.012 | 0.110 | 158 | (66) | 32 | 288 |
| *All cardiovascular patients* | | | | | | | | | |
| *2* | High fuel | 0.070 | (0.022) | 0.029 | 0.114 | 117 | (36) | 49 | 192 |
| *3* | Low fuel | 0.116 | (0.042) | 0.042 | 0.208 | 194 | (70) | 70 | 349 |
| | High fuel | 0.153 | (0.046) | 0.064 | 0.252 | 258 | (78) | 107 | 423 |
| *4* | Low fuel | 0.040 | (0.015) | 0.014 | 0.074 | 67 | (26) | 24 | 125 |
| | High fuel | 0.116 | (0.035) | 0.050 | 0.186 | 195 | (59) | 84 | 313 |
| *Cardiovascular patients over 65* | | | | | | | | | |
| *2* | High fuel | 0.087 | (0.029) | 0.033 | 0.148 | 134 | (45) | 51 | 229 |
| *3* | Low fuel | 0.143 | (0.054) | 0.053 | 0.268 | 221 | (83) | 82 | 414 |
| | High fuel | 0.190 | (0.060) | 0.075 | 0.317 | 294 | (93) | 116 | 490 |
| *4* | Low fuel | 0.049 | (0.020) | 0.016 | 0.095 | 76 | (30) | 25 | 146 |
| | High fuel | 0.144 | (0.046) | 0.059 | 0.237 | 222 | (71) | 91 | 366 |
| *All patients (respiratory + cardiovascular)* | | | | | | | | | |
| *2* | High fuel | – | – | – | – | 212 | (56) | 107 | 334 |
| *3* | Low fuel | – | – | – | – | 352 | (112) | 160 | 583 |
| | High fuel | – | – | – | – | 467 | (118) | 242 | 708 |
| *4* | Low fuel | – | – | – | – | 121 | (43) | 51 | 212 |
| | High fuel | – | – | – | – | 354 | (88) | 183 | 529 |

Lower/upper, bounds for 95% confidence interval.

$91 for the general population, approximately 82% of our lowest point estimate (low-fuel, zone 4), and 21% of our highest figure (high-fuel, zone 3). Similarly, converting Rittmaster et al.'s (2006) total cost estimate for morbidity effects of the 2006 Chisholm fire in Alberta, Canada, into 2008 U.S. dollars and a per-100 acre basis yields $150–$200.

It should be noted, however, that the latter study considers a much broader range of illness effects than ours, including symptom days and restricted activity days in addition to hospital admissions. Similarly, Butry et al. (2001) include emergency room visits, doctor's visits, and outpatient care in addition to inpatient treatment in their cost estimate. Furthermore, both studies consider a substantially larger affected population than our 350,000 residents of Reno/Sparks. As such, these existing estimates appear somewhat low compared to ours, even allowing for (possibly) large differences in treatment costs.

## Conclusion

To our knowledge this is the first study to relate daily fire progression and specific fire attributes to air quality and health impacts. The refined temporal level of analysis and the multi-year length of our time series for all three key variables – fire activity, air quality, and patient counts – allow for several extensions over existing models. These include the control of time-variant, confounding factors, the analysis of lagged smoke effects, and sensitivity checks regarding the role of wind patterns on smoke dispersion and transport.

Our results indicate that wildfire smoke can cause considerable health costs, in the magnitude of several million dollars per fire season. However, since our cost figures are based on inpatient treatment expenses alone and a single impact area, they are best interpreted as lower bounds of broader smoke-related health impacts associated with a given wildfire event or season. For example, some of the fires we consider in this study likely also affected communities along California's San Joaquin Valley corridor, such as Redding, Sacramento, Stockton, and Fresno. Together, these cities alone comprise a population of 1.4 million residents, close to five times more than live in Reno/Sparks. The entire valley is home to a population of over 4 million.

Naturally, the size of the impact area is only one of many factors that drive smoke-related health costs. As revealed by our analysis, an equally important factor is the effective duration of a fire, which is directly related to fire location vis-a-vis the target area and prevailing wind directions. Therefore, any across-the-board extrapolation of our cost estimates purely based on population size would likely be grossly misleading, given that relative fire bearing and prevailing winds can vary vastly across impact zones.

**Table A1**
Details for included wildfires.

| Name | State | Acres (000 s) | Start date | End date | Days | Distance (miles) | Fuel model |
|---|---|---|---|---|---|---|---|
| Comb Complex | CA | 8.7 | 7/23/2005 | 10/15/2005 | 85 | 196 | 9 |
| Crag | CA | 1.2 | 7/24/2005 | 7/29/2005 | 6 | 254 | 2 |
| Bootlegger | NV | 6.7 | 7/6/2006 | 8/13/2006 | 39 | 34 | 5 |
| Jackass | NV | 6.3 | 7/17/2006 | 7/21/2006 | 5 | 72 | 10 |
| Verdi | NV | 5.7 | 8/11/2006 | 8/13/2006 | 3 | 8 | 5 |
| Day | CA | 162.7 | 9/6/2006 | 10/2/2006 | 27 | 345 | 4 |
| Ralston | CA | 8.4 | 9/5/2006 | 9/17/2006 | 13 | 59 | 10 |
| Bolli | CA | 0.7 | 5/22/2007 | 5/27/2007 | 6 | 129 | 10 |
| Antelope Complex | CA | 136.8 | 7/5/2007 | 7/13/2007 | 9 | 60 | 10 |
| Balls Canyon | NV | 0.9 | 7/10/2007 | 7/13/2007 | 4 | 17 | 2 |
| Hawken | NV | 2.7 | 7/16/2007 | 7/23/2007 | 8 | 4 | 5 |
| Tar | CA | 5.6 | 8/10/2007 | 8/16/2007 | 7 | 249 | 4 |
| North | CA | 2.2 | 9/2/2007 | 9/8/2007 | 7 | 366 | 4 |
| Lime Complex | CA | 99.6 | 6/20/2008 | 8/15/2008 | 57 | 204 | 10 |
| Klamath Theater | CA | 192.0 | 6/21/2008 | 9/30/2008 | 102 | 230 | 8 |
| Iron & Alps Complex | CA | 105.6 | 6/21/2008 | 9/1/2008 | 73 | 190 | 10 |
| Yolla Bolly Complex | CA | 89.7 | 6/21/2008 | 8/19/2008 | 60 | 171 | 2 |
| Shu Lightning Complex | CA | 86.5 | 6/21/2008 | 7/25/2008 | 35 | 152 | 10 |
| BTU Lightning Complex | CA | 59.4 | 6/21/2008 | 7/29/2008 | 39 | 87 | 10 |
| Canyon Complex | CA | 38.5 | 6/21/2008 | 8/14/2008 | 55 | 77 | 10 |
| American River Complex | CA | 20.5 | 6/21/2008 | 8/1/2008 | 42 | 53 | 10 |
| Basin Complex | CA | 147.1 | 6/21/2008 | 7/27/2008 | 37 | 252 | 4 |
| Yuba River Complex | CA | 4.3 | 6/21/2008 | 7/15/2008 | 25 | 54 | 10 |
| Corral | CA | 12.4 | 6/23/2008 | 7/7/2008 | 15 | 108 | 2 |

Beyond medical expenses, our cost estimates are likely just the tip of a much larger iceberg of total economic losses from wildfire smoke in downwind communities. Additional costs would include non-market components such as decreased productivity and forgone recreational opportunities (e.g. Rittmaster et al., 2006; Kochi et al., 2010).[22]

Our findings also present some indication that these smoke effects are indeed sensitive to fire attributes, such as fuel conditions and distance. However, this first look at marginal effects should only be considered a starting point for a more thorough examination based on richer, more accurate data. Specifically, our analysis reflects the limitations of fire data that are routinely collected and archived by land managing agencies. It is currently not standard practice to record smoke-relevant fire details, such as acres consumed, fuel model, and fire intensity on a daily basis. Thus, we are restricted to assign a single fuel type to an entire fire event, even for very large burns. Information for fire intensity (flame length) proved too fragmented and temporally and spatially imprecise to be of any practical use for our study.

In addition, the frequent practice of grouping and re-grouping of individual fires into "complexes" poses an additional challenge in tracking fire progression and attributes. Such groupings presumably facilitate interagency collaboration and cost sharing in fire suppression, but pose a serious hurdle to reliable data extraction.

We therefore strongly urge for the collection of uninterrupted, daily information on fire characteristics, perhaps using an initial set of selected "pilot" fires that are located upwind of large population hubs. This would generate data with *daily* variability in fuel type and fire intensity, an integral prerequisite for further refinements to our model. Fortunately – or regrettably – it appears that there will be no dearth of opportunities to collect such data in the near future, given recent trends in wildfire activity. The faster we learn about detailed fire behavior and resulting economic impacts, the more rapidly we can design efficient strategies to manage what is both an ecological necessity and a serious disturbance to human economic endeavors.

## Appendix A. Additional tables

See Tables A1-A3.

## Appendix B. Additional figures

See Figs. B1-B2.

[22] Naturally, as pointed out by a referee, a full cost-benefit analysis of fire prevention and/or fire containment would also need to consider the benefit side of wildfires, such as the replenishment of forest soil and the provision of ecological conditions that foster the germination of seeds for a variety of tree species.

**Table A2**
Fire statistics by distance and RDIR deviation.

| RDIR +/− | Distance (miles) | # Firedays | Fires | | Acres burned | |
|---|---|---|---|---|---|---|
| | | | Count | % High fuel | Total | % High fuel |
| 30 | 0–50 | 8 | 4 | 0 | 3670 | 0 |
| | 51–100 | 50 | 7 | 100 | 182,891 | 100 |
| | 101–150 | 6 | 2 | 50 | 2055 | 24 |
| | 151–200 | 52 | 4 | 50 | 179,201 | 59 |
| | 201–250 | 47 | 2 | 50 | 137,629 | 53 |
| | 251–300 | 0 | 0 | N/A | 0 | N/A |
| | > 300 | 0 | 0 | N/A | 0 | N/A |
| 60 | 0–50 | 17 | 6 | 0 | 9149 | 0 |
| | 51–100 | 59 | 7 | 100 | 215,660 | 100 |
| | 101–150 | 11 | 2 | 50 | 8334 | 6 |
| | 151–200 | 71 | 4 | 50 | 244,006 | 67 |
| | 201–250 | 78 | 3 | 67 | 241,190 | 38 |
| | 251–300 | 9 | 2 | 50 | 18,595 | 98 |
| | > 300 | 2 | 2 | 100 | 2033 | 100 |
| 90 | 0–50 | 49 | 8 | 0 | 19,274 | 0 |
| | 51–100 | 64 | 10 | 70 | 226,071 | 97 |
| | 101–150 | 15 | 2 | 50 | 13,044 | 5 |
| | 151–200 | 84 | 4 | 50 | 253,932 | 67 |
| | 201–250 | 93 | 3 | 67 | 271,810 | 35 |
| | 251–300 | 25 | 2 | 50 | 86,697 | 99 |
| | > 300 | 11 | 2 | 100 | 46,397 | 100 |
| 120 | 0–50 | 54 | 8 | 0 | 20,095 | 0 |
| | 51–100 | 68 | 10 | 70 | 242,119 | 97 |
| | 101–150 | 15 | 2 | 50 | 13,044 | 5 |
| | 151–200 | 115 | 4 | 50 | 283,772 | 68 |
| | 201–250 | 98 | 3 | 67 | 291,142 | 36 |
| | 251–300 | 32 | 2 | 50 | 120,564 | 99 |
| | > 300 | 23 | 2 | 100 | 125,061 | 100 |

RDIR, resultant wind direction. See footnote 3 for a detailed definition.

**Table A3**
Identified fire days by RDIR deviation, distance, and fuel type.

| Distance | High fuel | Low fuel | All | Distance | High fuel | Low fuel | All |
|---|---|---|---|---|---|---|---|
| | RDIR+−30 | | | | RDIR+−60 | | |
| Zone 1 | 0 | 4 | 4 | Zone 1 | 0 | 12 | 12 |
| Zone 2 | 11 | 0 | 11 | Zone 2 | 12 | 0 | 12 |
| Zone 3 | 5 | 4 | 12 | Zone 3 | 6 | 5 | 12 |
| Zone 4 | 0 | 11 | 11 | Zone 4 | 3 | 18 | 21 |
| All | 22 | 20 | | all | 23 | 37 | |
| | RDIR+−90 | | | | RDIR+−120 | | |
| Zone 1 | 0 | 40 | 40 | Zone 1 | 0 | 44 | 44 |
| Zone 2 | 10 | 2 | 12 | Zone 2 | 6 | 3 | 9 |
| Zone 3 | 5 | 11 | 17 | Zone 3 | 5 | 38 | 43 |
| Zone 4 | 13 | 18 | 31 | Zone 4 | 23 | 18 | 41 |
| All | 31 | 77 | | all | 41 | 109 | |

It should be noted that the "all" columns and rows in Table A3 do not necessarily indicate the exact sum of "high fuel" and "low fuel" days, since fuel-specific days may overlap within a given zone. For example, at $d=90$, a total of 17 effective fire days are identified for zone 3. However, on one of these days one or more low fuel and high fuel fires coincide. Thus, the *separately* identified low fuel and high fuel days only add up to 16.
RDIR, resultant wind direction. See footnote 3 for a detailed definition.

## Appendix C. Criteria for the specification search for the $PM_{2.5}$ model

Our intuitive criteria to select the best mix of RDIR deviations and lags for effective acres burned in the four distance zones were as follows: (i) any setting of $d$ that produces significant *negative* current or lagged marginal effects of effective

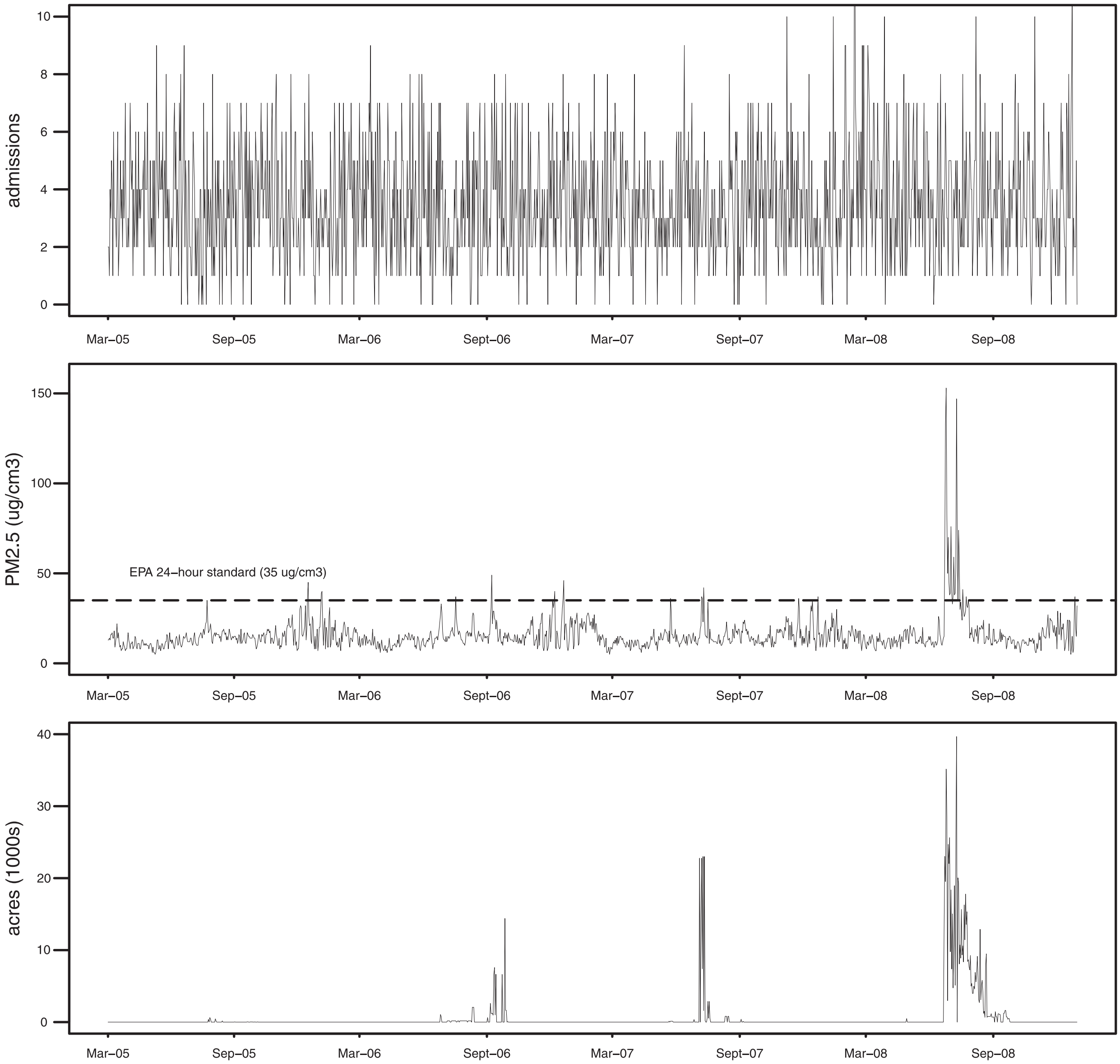


**Fig. B1.** Cardiovascular admissions, $PM_{2.5}$, and acres burned, 2005–2008.

acres on $PM_{2.5}$ levels cannot be meaningful. Such negative effects can arise if too many irrelevant fire days are included, such that low levels of $PM_{2.5}$ correlate with erroneously high levels of effective acres, or if too many relevant days are excluded, such that high levels of $PM_{2.5}$ coincide with erroneously low levels of daily effective acres. (ii) The deviation criterion cannot be "tighter" for more remote distance zones compared to nearby zones. This is based on the intuition that more remote fires need longer time to send smoke to the impact area. This exposes the plume to more hourly variability in wind patterns, calling for a more relaxed RDIR deviation. (iii) More remote distance zones should include no fewer lags than zones closer to the target area. (iv) The RDIR deviation cannot be tighter for higher lags. (v) The same number of lags and RDIR deviations are applied to both fuel types within a distance zone. (vi) The cumulative impact (over all lags) for low fuel burns cannot exceed that of high fuel burns within the same distance zone, since this suggests that more current smoke from high fuel burns might be erroneously interpreted as lagged smoke from low-fuel burns, or vice versa. (vii) Competing models that are plausible in all other respects are evaluated based on model fit, using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Mean Squared Error (MSE).

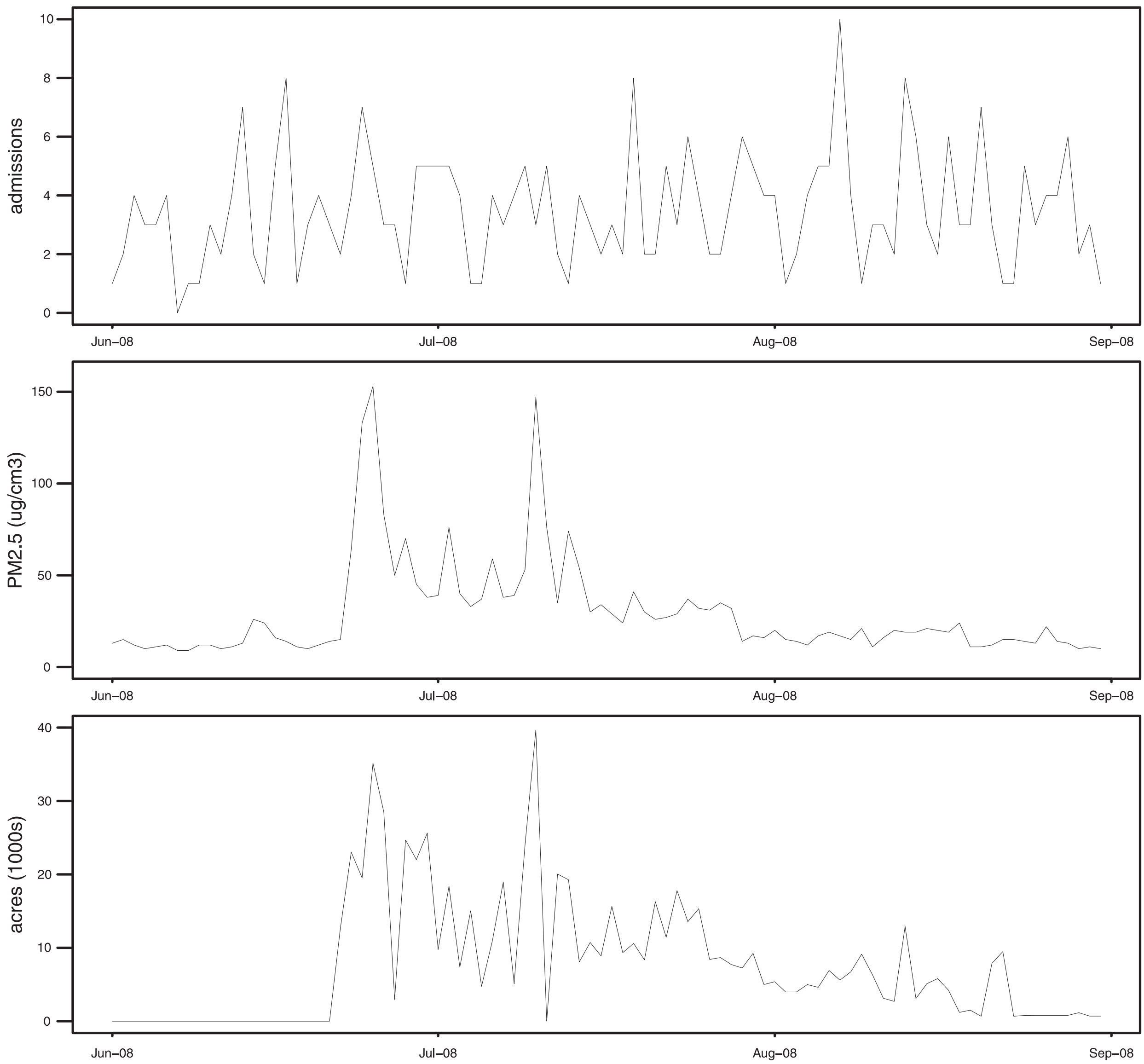


**Fig. B2.** Cardiovascular admissions, $PM_{2.5}$, and acres burned, summer 2008.

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