Blowing Smoke: Health Impacts of Wildfire Plume Dynamics[1]

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Abstract. Long-range transport of wildfire smoke affects air quality on a broad geographic and temporal scale. Using a novel satellite-based dataset that allows us to observe daily smoke plume coverage for almost every location in the U.S. from 2006 to 2013, we find that transport of wildfire smoke generates frequent and significant variations in air pollution, especially fine particulate matter, for cities hundreds of miles away from the fire itself. We link this variation to Medicare administrative data to provide the first national-scale evaluation of the health cost of wildfire pollution among the U.S. elderly. We show that wildfire smoke exposure poses a significant mortality risk for the elderly. The effect concentrates among individuals who live in areas with generally low background levels of air pollution. We find strong and consistent evidence that smoke exposure also increases healthcare use and spending.

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1. Introduction

Wildfires are widely recognized as major contributors to air pollution, contributing approximately 15 percent of total US particle emissions each year. This is more than the emissions from power plants and transportation sectors combined.[2] Despite the obvious health threats that wildfires pose, the literature faces two challenges in credibly establishing the health consequences of wildfire pollution exposure. First, wildfire smoke can travel long distances—hundreds or even thousands of miles—and persist for days or even weeks. The lack of ability to track wildfire smoke movement and to measure health outcomes on a population scale have forced many previous studies to focus on communities in the immediate vicinity of fires. Second, previous research often studies intensive air pollution events from unusually large wildfires, whereas the average wildfire is small in scale, burning less than 100 acres of land. Because the literature has failed to make use of evidence from smaller but more frequent burnings and to include the impact of both small and large fires on distant locations in its assessment, there is to date a dearth of evidence on the level of population's wildfire pollution exposure and the health cost of exposure.

In this paper, we provide the first national-scale evaluation of the health impact and healthcare cost of exposure to wildfire smoke. Our beginning point is a novel dataset of wildfire smoke plumes. This data comes from an operational group of National Oceanic and Atmospheric Administration (NOAA) experts who rely on satellite imageries to identify the location and the movements of every wildfire smoke plume in the US. Using this data, we derive daily smoke exposure status for almost every location in the US. To study the health effects of smoke exposure, we link this data to daily health and healthcare spending data derived from administrative records for the universe of Medicare beneficiaries over the years 2005 – 2013. This novel link gives us three primary advantages over the previous literature. First, both the satellite-based smoke data and the Medicare data contain information with a high level of spatial and temporal granularity. We are able to conduct analysis with a sample of over 86 million observations at the 5-digit ZIP Code by day level. Among many other advantages, the large sample size gives us adequate statistical power to precisely identify smoke's effects on highly rare but important health events, such as mortality. Second, the data allows us to exploit quasi-random variation in air quality triggered by drifting smoke plumes. Our empirical strategy exploits year-to-year variation in whether a specific area is covered with smoke on a specific time of year to identify the causal impact of smoke. Third, the Medicare data gives us information on a range of health events, such as emergency room visits, hospitalization, and outpatient visits, within the same study population. This allows us to provide much more consistent and richer characterization of the

[2] Source: US EPA Air Pollutant Emissions Trends Data < https://www.epa.gov/air-emissions-inventories/air-pollutant-emissions-trends-data>

costs of wildfire pollution than was previously possible. For example, we are able to directly compare the magnitude of the mortality cost versus the healthcare cost of smoke.

Our analysis yields four main sets of findings. First, we use the satellite data to characterize wildfire smoke exposure in the US. We find wildfire smoke exposure is a widespread and recurrent hazard. Although wildfires are most prevalent in the west, wind transport of smoke-borne pollution affects a large portion of the country, with the typical US citizen being exposed to an average of 23 days of smoke per year. To further characterize smoke exposure, we relate the smoke data to two independently developed datasets. We first link it to wildfire records from wildland management and firefighting agencies. We find that on a smoke day a city is on average over 300 miles away from the nearest burning, suggesting the average smoke shock is generated from a distant fire. We then link smoke to the US EPA's ground pollution monitoring data, and we show that the average smoke shock creates a transient but significant increase in air pollution, particularly the ambient fine particulate matter pollution ($PM_{2.5}$). On average, we find that $PM_{2.5}$ increases by about 2 ug/m^3 on a smoke day when the daily average is roughly 11 ug/m^3. Such an increase lasts for roughly 3 days before it dies out.

Second, we find wildfire smoke causes a significant increase in elderly mortality. On a typical smoke day, the mortality rate jumps up by 0.522 deaths per million Medicare beneficiaries exposed, which represents a 0.4 percent increase. Importantly, even in the elderly population we examine, we find no evidence of short-run mortality displacement or "harvesting" in the smoke-mortality relationship. This is the concern that a naïve mortality count would tend to overestimate the true mortality cost of a health shock (such as smoke exposure) if those killed by shocks are likely to be among the frailest individuals in the population and likely to die within a few days or weeks, anyway. Contrary to the harvesting hypothesis, we find exactly the opposite: mortality effects tend to *increase* as the post-event window increases in length. Employing an estimation framework that examines mortality in a multi-day look-forward window, we find that the effect of a day of smoke increases to 1.204 deaths per million over a 3-day window (the smoke day and the 2 following days) and 1.434 deaths per million over a 7-day window. Therefore, contemporaneous-run estimates likely only partially capture the total impact of pollution exposure.[3]

Third, using the detailed information on healthcare use and cost for individuals enrolled in traditional (fee-for-service) Medicare, we investigate the impact of smoke on emergency department visits, hospital admissions, and general inpatient and outpatient healthcare spending. We find strong and consistent evidence that smoke exposure causes increased healthcare use and spending. This positive relationship is

[3] To be clear, such a pattern could be generated by a model where smoke both accelerates the death of very frail individuals and has delayed effects that manifest only over days or weeks. However, the fact that we do not see a rebound in the mortality effect as the post-event window increases suggests that our results are not only due to harvesting.

present for overall admissions and spending as well as for cause-specific admissions for circulatory and respiratory causes, which are thought to be most sensitive to pollution.

Fourth, we explore heterogeneity in mortality responses to smoke. Relatively little is known about the shape of the relationship between pollution exposure and health, both in terms of how the health effects vary with the size of an acute shock and how the effect of the same size shock varies with background pollution levels. Investigating these issues is complicated by the fact that the size and frequency of smoke exposure is often related to baseline pollution levels. The smoke exposure natural experiment provides a method of addressing these questions. Exploiting the fact whether an area is exposed to smoke and the size of the pollution impact of smoke exposure is largely independent of an area's general characteristics, we ask whether the marginal effect of the *same* pollution exposure depends on whether the exposed area is generally polluted or not. We show that (1) how often an area is exposed to smoke is uncorrelated with average baseline $PM_{2.5}$ levels, (2) the marginal effect of smoke on $PM_{2.5}$ is uncorrelated with average $PM_{2.5}$ levels, but (3) the mortality effect of smoke is significantly larger in places with low average levels of $PM_{2.5}$. Importantly, we find that such heterogeneity is not explained by differences in income levels.

While this exercise does not directly speak to the mechanism underlying the heterogeneity, the finding may have policy implications. For example, a disproportionately large amount of resources are allocated to protect public health against pollution exposure in regions where air pollution level exceeds the US EPA's national $PM_{2.5}$ standard. However, we show that, at least when exposed to *transient* pollution variations, there is no evidence that individuals living in these highly-polluted regions experience significant mortality effects. While quantifying the benefits of reducing the *average* level of pollution is beyond the scope of this study, our results do suggest that resources may be deployed more effectively to reduce pollution shocks in less-polluted areas.

We contribute to the literature in three primary ways. Our study provides the first characterization of wildfire smoke exposure in the US using direct observation of smoke plumes. While the current understanding on wildfire exposure has focused on the prevalence and spatial distribution of *fires*, we highlight two significance of wildfire *smoke* exposure. First, we show that wildfire smoke is far from a remote risk that matters only for population living near forests. An average population in our sample is exposed to more than 3 weeks of smoke per year generated by fires hundreds of miles away; some regions with the most severe smoke exposure has few or no fires at all. Second, smoke generates transient but significant increase in air pollution. As a potential exacerbation of the smoke's health hazard, the extent of the average pollution increase on a smoke day is unlikely to cause any visual impact on the air, and therefore may not trigger significant public attention and protection.

Our paper also delivers the first causal estimates of wildfire smoke's health costs on a national scale. Previous literature – primarily consists of case studies of intensive fires – often struggles to achieve adequate statistical power because severe outcomes such as mortality or hospitalization are rare, as are wildfire occurrences (for reviews, see e.g., Liu et al., 2015; Reid et al., 2016).[4] A small number of studies have considered the link between smoke exposure and mortality but have generally been unable to document a positive association.[5] Measurement of exposure also varies across studies, from focusing on neighborhoods in the immediate vicinity of the burning area, to the use of global pollution transport model to predict wildfire pollution (e.g., Liu et al., 2017).[6] Overall, the previous literature has provided inconclusive evidence regarding the relevance of wildfire smoke's health impacts, despite the fact that the link between wildfire smoke and air pollution including particulate matter exposure is well-established (Reisen et al., 2015), as is the link between particulate matter and mortality (Deryugina et al., 2016; Zanobetti and Schwartz, 2009). For example, Liu et al. (2015) report that of the 14 studies they review that considered the relationship between wildfire smoke and cardiovascular morbidity, only six reported positive associations, while Reid et al. (2016) summarize the literature as "inconsistent." By using direct satellite observation to estimate a long panel and look at both mortality and healthcare consequences within the same estimation framework, our results may help reconcile evidence from previous literature.

Finally, our paper is related to the developing literature on the causal link between short-term exposure to air pollution and adverse health outcomes such as increases in health care utilization (Moretti and Neidell, 2011; Schlenker and Walker, 2015) and mortality (Deryugina et al., 2016; Knittel, Miller, and Sanders, 2016). Our results demonstrate both visually and statistically how a transient pollution dynamics

[4] The strongest links between smoke exposure and health are for respiratory disease related primary care visits, emergency department visits and hospital admissions. Evidence supporting cardiovascular responses is somewhat mixed. Some but not all studies found evidence suggesting a positive association between smoke exposure and conditions such as acute myocardial infarction, congestive heart failure, ischemic heart disease. For reviews, see e.g., Liu et al. (2015) and Reid et al. (2016).

[5] Vedal and Dutton (2006) study the impact of a large smoke plume that affected the Denver area in 2002 and find no increase on mortality in Denver relative to nearby control areas that were not affected by smoke. Zu et al. (2016) analyze the impact of large forest fires in Quebec in 2002, which generated a large smoke plume that covered the Boston and New York City areas and did not find evidence of mortality increases in either of these regions. One paper that does mortality effects is Jayachandran (2008), who studies the impact of very large wildfires that covered Indonesia in smoke in 1997 and concludes that prenatal exposure to smoke during these events accounts for a significant portion of the "missing children" in the 2000 Indonesian Census, although it is not clear whether this is a result of lower birth rates or decreased survival after birth.

[6] Liu et al. (2017) examine the relationship between particulate matter exposure driven by wildfire pollution and hospital admissions. Like our study, Liu et al. (2017) use Medicare data, although they look at a shorter and slightly different period (2004 – 2009), conduct their analysis at the county level rather than the ZIP Code level, and only consider the Western United States. Methodologically, they rely on a global pollution transport model to identify pollution variation caused by smoke. For their main results, they do not observe an association between smoke exposure and respiratory or cardiovascular hospital admissions overall, although they do find an effect on respiratory admissions on days when smoke-induced pollution is particularly high.

translate into a broad set of health responses. More generally, our study points to wildfire smoke as a source of pollution variation that can potentially be used in other settings to study causal effects of air pollution.

The paper proceeds as follows. Section 2 describes the primary data sources. Section 3 characterizes wildfire smoke exposure in the US. Section 4 explains the empirical strategy used to estimate the causal effects of wildfire smoke. Section 5 presents the air pollution and mortality effects of wildfire smoke. Section 6 presents the healthcare spending effects of wildfire smoke. Section 7 concludes.

2. Primary Data Sources

2.A. Wildfire, Smoke Plumes, and Air Pollution Data

Our smoke data come from the National Oceanic and Atmospheric Administration’s Hazard Mapping System (HMS). Every day, HMS smoke analysts incorporate information from animated satellite imageries to produce geo-referenced outlines that reflect their best estimate of the location of all smoke plumes observed across the U.S. The drawing is usually performed twice a day, once shortly before sunrise, and once shortly after sunset, giving us daily summaries of wildfire smoke exposure from August 2005 to December 2013. In rare cases where a smoke plume is believed to originate from sources outside of the satellites' range of observation, e.g. plumes approaching the West Coast from the Pacific, a smoke transport model is used to determine the source fire in order to help drawing. However, the majority of data production is based solely on satellite imageries and the analysts' visual screening.

We complement the smoke data with two ground-based measurements. First, we obtain wildfire records obtained from seven major wildland and fire management agencies.[7] This data contains detailed information on time and location of wildland fire, which we use to provide validation to the satellite smoke measure. Second, we draw pollution monitor readings from the US EPA's Air Quality System (AQS). These data contain daily pollutant concentration readings at the individual station level. We measure pollution reading at the ZIP Code level by spatially averaging readings from all monitors within 20 miles of the ZIP Code centroid, with inverse of distance as weights. Whereas we focus on $PM_{2.5}$ pollution in this paper, wildfire smoke is also understood to contain other pollutants. We therefore obtain monitoring data on $PM_{2.5}$ and five other “criteria air pollutants” as defined by the U.S. EPA, including coarse particulate matter (PM_{10}), ozone (O_3), carbon monoxide (CO), nitrogen dioxide (NO_2), and sulfur dioxide (SO_2).

[7] Bureau of Indian Affairs, Bureau of Land Management, Bureau of Reclamation, California Department of Forestry and Fire Protection, National Park Service Fire and Aviation Management, US Fish & Wildlife Service, and Forest Service.

2.B. Health Outcomes Data

Our health and healthcare data come from Medicare administrative records. We obtain access to the Medicare Master Beneficiary Summary File, an annual directory which allows us to observe enrollment status and individual characteristics of 100% of eligible Medicare Beneficiaries, including both traditional fee-for-service Medicare and Medicare Advantage managed care. For each year, we observe beneficiaries' ZIP Code of residence, and for decedents, we observe date of death. Importantly, for the vast majority of beneficiaries, Medicare data's date of death field is verified with the Social Security Administration, allowing us to measure mortality accurately. Using these information, we build daily mortality rate for beneficiaries aged 65 or plus at the ZIP Code level from 2005 to 2013.

Whereas we use mortality rate as our baseline measure of health in this study, we also create a set of measures of health care utilization. We focus on the subset of beneficiaries enrolled in the fee-for-service Medicare (FFS). These make up about 75 percent of the population in our study sample. We obtain access to the Medicare Provider Analysis and Review File (MEDPAR) based on the accumulation of service claims corresponding to a particular stay. The dataset contains information on the date of admission, length of stay, and total cost associated with each stay. Each stay is associated with a field that identifies the beneficiary involved, which allows us to link to individual characteristics, such as ZIP Code of residence, in the Master Beneficiary Summary File. From this data, we build daily hospitalization rate and cost at the ZIP Code level. Next, we access the Medicare Information on Outpatient Services Standard Analytical File (Outpatient SAF) which contains the universe of outpatient claims submitted by institutional outpatient providers, and include information on the date of service and associated cost. Finally, from the MEDPAR and the Outpatient SAF files, we observe emergency room visits that both end up with hospitalization or not.

3. Exposure to Wildfire Smoke in the U.S.

In this section we summarize wildfire smoke exposure in the U.S. While our analysis data contains millions of wildfire smoke events, it helps to begin with one example, the 2013 Rim Fire in central California, to illustrate the wildfire pollution problem, the challenges that existing research faces, and this paper’s approach.

The Rim Fire is believed to have been ignited by a hunter who illegally started a campfire that eventually went out of control.[8] The fire began on August 17, 2013 and was not contained until October 24, 2013. It continued to burn for over a year before it was declared fully extinguished. One of the largest fires in the US history, the Rim Fire consumed over 257,000 acres of land and the suppression cost $127 million.[9] Figure 1, Panel A is a satellite image showing of the Rim Fire's pollution on August 22, 2013, as well as the location of two major cities in the area: Reno in Nevada, and San Jose in California. The image shows that winds from the south blow smoke from the Rim Fire to Reno. Figure 1, panel B shows that the smoke raised Reno's level of fine particulate matter pollution ($PM_{2.5}$) in the air to over 60 ug/m^3, close to the level observed in Beijing. In contrast, the city of San Jose, which is almost equally distant to the fire but located to the southeast of the burning area, observed no significant changes in air quality over the same time period. Of course, the Rim Fire represents one of the largest fire and pollution events; the *average* wildfire smoke event in our data leads to much less severe air pollution consequences. However, the nature of the pollution shock is similar: difference in exposure are driven mainly by shifting wind patterns, and smoke exposure is transient, elevating the level of pollution for a number of days before it clears out.

Figure 2 plots the development of the Rim Fire over six days soon after it erupted and provides a series of day-to-day snapshots that represent the format of our smoke plume data. The figure highlights two typical challenges with the existing literature and how we approach them with our data. First, wildfire smoke does not only affect communities near the fire. Smoke plumes can rise 1 – 3 miles into the atmosphere and travel thousands of miles from the originating fire (Reisen et al., 2015). Figure 2 shows that the Rim Fire's smoke indeed traveled quite far, covering much of the northwest US after a few days. The smoke data therefore allows us to capture exposure to the Rim Fire's smoke for cities far away from the fire itself. Second, while large fires are not uncommon, the typical fire is small. Over the past two decades, the National Interagency Fire Center has identified an average of around 74,000 fires with the average fire burns around 80 acres.[10] We can see this in Figure 2 which picks up numerous smaller fires in addition to the Rim Fire. While the scale of these fires are much smaller than the Rim Fire, our smoke data suggests that they nevertheless generate significant smoke plumes that travel long distances.

Figure 3 summarizes average wildfire exposure. The maps plot the average number of wildfire (panel A) and the average number of wildfire smoke days (panel B) by 5-digit ZIP Code over the period 2005-2013. Although in the United States wildfires are most prevalent in the west, wind transport of smoke-

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[8] See < http://www.latimes.com/local/la-me-rim-fire-20140808-story.html>

[9] www.fs.usda.gov/detail/stanislaus/home/?cid=stelprd3824723

[10] There is substantial variation in the magnitude of fires. For example, between 2012 and 2016, on average about around 1000 fires (1.5 percent) were classified as large (burning over 100 acres of timber or 300 acres of grass and brush), and around 30 fires each year were classified as significant, burning over 40,000 acres. See, e.g. https://www.nifc.gov/fireInfo/fireInfo_stats_totalFires.html

borne pollution affects a large portion of the country. More statistics are reported in Table 1, panel A. We compute that the typical US citizen being exposed to an average of 23.3 days of smoke per year. Data suggests that the average smoke event is created by distant fires: on days when the satellite detects smoke coverage in a ZIP Code, the nearest wildfire is roughly 383 miles away according to the fire registry data.

4. The Effect of Wildfire Smoke on Air Pollution, Mortality, Healthcare Use and Spending

4.A. Empirical Strategy

We analyze the effect of wildfire smoke exposure in two ways: visually in event-study style graphs and also using regression analysis. For the event-study analysis, , we take all 6.5 million ZIP Code-daily level smoke events and simply plot means of the outcome variables in the days before and after the smoke day. We remove secular components by including 366 day-of-year dummies and 7 day-of-week dummies, and with no other controls. The simplicity of this event study style exercise allows us to examine break in trends by looking at an extensive time window around the occurrence of smoke events. In our analysis, we plot outcomes for 20 days before and 20 days after the smoke day.

In our regression analysis, we develop a panel estimation model to estimate the reduced form effect of a day of wildfire smoke exposure. Since both smoke, pollution, and health may exhibit geographic and seasonal patterns, we use an identification strategy that explores year-to-year variation in smoke exposure within the same areas and during the same season of the year, we use an identification strategy that explores year-to-year variation in smoke exposure within the same areas and during the same season of the year. Let Y_{zt} be outcome in ZIP Code *z* on date *t*. Our primary estimation equation is

$$Y_{zt} = \sum_{d=-7}^{6} \boldsymbol{\beta_d} \cdot Smoke_{z(t-d)} + \underbrace{\alpha_z \times WeekYr_t}_{\substack{ZIP\ Code\ by\ week-of-year \\ FEs}} + \overbrace{State_z \times Year_t}^{\substack{state\ by\ year \\ FEs}} + \underbrace{DayWeek_t}_{\substack{day-of-week \\ FEs}} + X_{zt}\gamma + \varepsilon_{zt} \qquad (1)$$

Our treatment variable is $Smoke_{zt}$, which is an indicator equals to 1 if the ZIP Code-day is covered by smoke, and 0 otherwise.[11] We include 7 smoke leads ($Smoke_{z(t+7)}$, …, $Smoke_{z(t+1)}$) and 6 smoke lags ($Smoke_{z(t-1)}$, …, $Smoke_{z(t-6)}$) in the regression. Together with the contemporaneous smoke indicator ($Smoke_{zt}$), these coefficients trace out the effect of smoke exposure in the week before and the week after the smoke day. Inclusion of leads and lags also addresses serial correlations in smoke exposure. While our table estimates focus on the coefficient on the contemporaneous smoke term $Smoke_{zt}$, we also plot leads and lags of smoke exposure as a second piece of visual evidence in addition to the simple event study analysis.

The key set of controls are the ZIP Code by week-of-year fixed effects which ensure that the comparison is done within the same ZIP Code on the same week of the year, but across years with different smoke exposure. We further control for state by year effects to capture variation in factors such as changes in state policies. Day-of-week effects capture any secular trend in the outcomes at the day-of-week level. For example, hospital admissions exhibit strong weekday vs. weekend pattern. Therefore, our primary specification includes 1.5 million ZIP Code by week-of-year dummies, 440 state by year dummies, and 7 day-of-week dummies. In addition, we address the omitted variable bias concern that weather elements, such as temperature and precipitation, may interact with air pollution and at the same time have direct impact on health outcomes (Deschenes and Greenstone, 2011; Barreca, Clay, Deschenes, Greenstone, and Shapiro, 2016; Heutel, Miller, and Molitor, 2017). We use weather station data from the Global Historical Climatology Network and compute temperature and precipitation for each ZIP Code-day. We control for a step function in daily temperature, allowing the mortality effect to vary arbitrarily by 10-degree Fahrenheit bins. We also control for a quadratic term in daily precipitation. These controls are included in the time-variant control matrix X_{zt}. While this is a relatively large number of controls, our main regression sample includes 84 million observations, leaving the estimation model with sufficient degrees of freedom.[12]

Finally, we weight the regression using number of beneficiaries alive in each ZIP Code-date cell so that our estimates reflect the experience of a representative beneficiary. In subsequent analysis we report

[11] We define a ZIP Code to be covered by smoke if any part of it intersects smoke plumes on a given day. In the appendix, we report a robustness check that defines exposure by the ZIP Code being entirely covered in smoke ("deep" exposure). This robustness specification produces slightly larger results across almost every pollution and health outcome, potentially because the exposure is stronger.

[12] In the appendix, we report specification checks where we either reduce the number of fixed effects controls, e.g. using plain ZIP Code, year, week-of-year, day-of-week fixed effects, or apply more stringent identifications, e.g. allowing ZIP Code fixed effects to vary arbitrarily by each day-of-year, including county-by-year fixed effects, or including date (year by day-of-year) fixed effects. Overall, these robustness checks produce similar results. Another concern with the smoke quasi-experiment is that wind currents might carry both wildfire smoke and other atmospheric pollution to downwind cities. In the appendix, we show that are results are robust to including wind direction-by-state fixed effects. To the extent that most industrial pollution is from geographically fixed sources, these fixed effects should help to separate out health impacts from industrial pollution transport.

standard errors clustered at the county level. Our findings are not sensitive to more flexible forms of clustering, such as two-way clustering at both the county and the date level.

4.B. Air Pollution Effects

We begin by examining the impact of smoke on the concentration of air pollution measured by ground-based pollution monitors. We first focus on $PM_{2.5}$ which is best known as the main pollutant of wildfire emission. Panel A of Figure 4 shows that, both in the raw plot and in the lead/lag plot, the occurrence of smoke on day 0 corresponds to a clear spike in $PM_{2.5}$ levels. Smoke's effect on air quality is transient: the increase in the level of $PM_{2.5}$ last for about 3 days before returning to the pre-period level. There is some evidence that $PM_{2.5}$ increases on the day before smoke exposure. This may due to (1) serial correlations in daily smoke and pollution, and/or (2) measurement error in the smoke measure, as the data only captures smoke status at the instant when the satellite picture is taken. This evidence also suggests that it is important to include lead/lag terms in the regression analysis.[13]

Table 2 reports the effect of smoke on air pollution (i.e. the β_0 coefficient in equation (1)) after controlling for lead/lag smoke. Column 1 shows that, on the smoke day, $PM_{2.5}$ rises by roughly 2.3 ug/m^3, relative to a daily mean of 10.7 ug/m^3. By current standard established in the Clean Air Act, the daily safety concentration level is 35 ug/m^3. Therefore, wildfire smoke provides a mild but meaningful shock to air quality. Smoke also increases the concentration of other air pollutants. Table 2 reports responses of other five "criteria pollutants" used by the EPA to characterize ambient air quality. Point estimates in column 2 through 6 show that the impact of wildfire smoke on other criteria pollutants are significant, although they are smaller in magnitude. Concentrated increases are observed for coarse particulate matter (PM_{10}) which is another direct emission of wildfire, and ozone (O_3) which is the product of chemical reactions between fire-emitted pollutants or background pollutants in the atmosphere.

The evidence that wildfire smoke increases air pollution in distance cities is important for interpreting our health impact estimates as driven by wildfire pollution. Beside pollution exposure, wildfire may affect health outcomes through a number of mechanisms such as injury, property damage and evacuation. However, these external mechanisms are unlikely to matter for our estimation when the average smoke exposure is experienced hundreds of miles away from the fire itself.

[13] Without smoke leads and lags, we obtain larger coefficient estimates for pollution, mortality, and healthcare use; on the other hand, our main conclusions are not sensitive to having more leads and lags, e.g. 20 smoke leads and 20 smoke lags. These results are reported in the Appendix.

4.C. Mortality Effects

Panel B of Figure 4 plots the impact of smoke on mortality for all Medicare beneficiaries over age 65. Again, in both the raw plot and the lead/lag plot, the mortality rate exhibits a flat and stable trend in the 20 days before smoke exposure, followed by a discrete increase on the day when smoke hits. The size of the jump is roughly 0.5 extra deaths per million beneficiaries. The graph provides visual evidence of that the impact of smoke on mortality lasts for days, with excessive mortality visually concentrated in the first 3 days after the smoke shock. However, the lead/lag plot on the right illustrates that these effects essentially disappear by 7 days after the shock. This pattern motivates econometric specifications that are able to capture delayed causation, which we describe in detail below.

Table 3, panel A presents regression results of the impact of smoke exposure on elderly mortality. For future reference, we repeat the $PM_{2.5}$ estimates in column 1. Column 2 shows that the contemporaneous (1-day) mortality rate increases significantly by 0.522 per million beneficiaries on a smoke day. Reassuringly, the magnitude of this effect is similar to that seen in Figure 4. The magnitude of the contemporaneous mortality consequence of wildfire smoke is moderate. Our estimate implies 21 excessive deaths among the Medicare beneficiaries on a smoke day (0.522 additional deaths per million people multiplied by 40.5 million Medicare beneficiaries). Based on satellite observations, a typical Medicare beneficiary is exposed to 23.3 smoke days per year, implying 489 annual deaths of beneficiaries due to wildfire smoke. In comparison, previous studies looking at the elderly population estimate that extreme heat (> 90° F days) related annual premature deaths range from 1,000 to 3,000 (Deschenes and Greenstone, 2011; Barreca, Clay, Deschenes, Greenstone, and Shapiro, 2016; Heutel, Miller, and Molitor, 2017).

Focusing on the contemporaneous mortality effect of smoke can mask the true impact of pollution exposure. On the one hand, if pollution exposure "harvests" the lives of the unhealthiest individuals, contemporaneous mortality effects overestimate the true cost of pollution since those who are killed by pollution were likely to die soon, anyway. Alternatively, if the health effects of pollution is persistent, individuals might survive the initial exposure but get killed as the impact manifests over time. In this case, same-day mortality counts fail to capture the full cost of pollution exposure. This is likely to be the case in our setting, as suggested by the visual pattern presented in Figure 4.

To test these hypotheses, we repeat the mortality regressions but replace the dependent variable with mortality in the next 3- and 7-day look-ahead windows. For example, if January 1st, 2013 is a smoke day, our 3-day effect estimates capture the effect of smoke on mortality that takes place within the three days between January 1st to January 3rd, 2013. Notice that, although an smoke episode may last for a couple of days, since we control for 7 smoke leads and 6 smoke lags in all regressions, the effect estimate reflects the mortality effect of today's smoke in the look-ahead window. Therefore, if the contemporaneous impact of mortality is driven by "harvesting", i.e. displacing forward deaths that would have occurred anyway in the next couple of days, one would expect the multi-day mortality effects to be zero. On the other hand, if the effect of smoke develops over time, then the multi-day coefficients are expected to grow in size.

Table 3, Panel A, columns 2 – 4 present results for 1-day, 3-day and 7-day event windows. They indicate that the mortality impact of smoke exposure grows over time, and therefore that the 1-day estimate understates the true cost of smoke exposure. The point estimates of mortality effect grows from 0.522 on the smoke day (column 2) to 1.204 deaths per million over the 3-day window (column 3). Put differently, the estimate suggests that, in addition to its mortality impact on the initial exposure day, smoke leads to about 0.682 deaths per million over the next two days. The 7-day mortality estimate in column 4 suggests that beyond the third after since exposure, there are few additional deaths caused by the smoke. This result is consistent with the visual evidence in Figure 4. Importantly, the coefficient estimate does not decrease and remains significantly different from zero, suggesting the mortality impact we find is not only due to short-term displacement of deaths that otherwise would have occurred in the next week. Using the 7-day estimate, we calculate that the effect aggregates to an annual of 1,353 premature deaths due to wildfire smoke exposure.

4.D. Healthcare Use and Spending Effects

We now examine the impact of wildfire smoke exposure on healthcare use and spending. Recent literature employs administrative records on hospital discharge records to estimate the effect of pollution. However, inpatient use likely capture only individuals who require the most intensive care, constituting an incomplete measure of illness. Importantly, discharge records may miss outpatient emergency department visits that do not result in admission. For example, it may miss outpatient health care resources that individuals spent to avert the health consequence of pollution exposure. Without such spending, these individuals could have ended up with inpatient encounters.

4.D.1 General Health Care Utilization Effects

We access the universe of the Medicare's institutional claims for both inpatient and outpatient utilization among the FFS population, which allows us to paint a more comprehensive picture on healthcare costs.[14] In our baseline analysis, we define healthcare utilization rate as the sum of hospital

[14] Currently, we do not have access to the universe of claims in non-institutional settings, e.g. physician offices.

admission rate in inpatient setting and emergency room visit rate in outpatient setting. Panel C of Figure 4 presents the impact of smoke on healthcare utilization. Again, there is a clear spike in utilization around the smoke day. Although there is some evidence of an upward sloping pre-trend in the raw plot, this trend disappears when controlling for lead/lags on the right. The graphical pattern suggests that smoke's impact on utilization concentrates in the day of exposure, and therefore in subsequent analysis we focus on same-day effect estimates where the outcome variable is 1-day utilization. Table 4, panel A, column 1 shows that overall use increases by 9.282 visits per million beneficiaries, representing a roughly 0.5 percent increase from the mean of 1,964.35. Columns 2 and 3 of panel A show that the utilization effect is explained by significant increases of around 0.5 percent in both hospital admissions and outpatient ER visits. Cutting the data in a slightly different way, column 1 of table 5 shows a similarly-sized effect on overall ER visits (including visits that end in admission and those that do not). Columns 2 and 3 of Table 5 show that these effects on use translate into effects on spending. While the inpatient spending estimate is roughly in line with the 0.5 percent increase in admissions, the outpatient spending variable is significantly larger, at almost 3 percent of the mean. This suggests that the marginal outpatient visit caused by smoke is relatively expensive.

4.D.2 Health Care Utilization Effects by Diagnosis

We have shown that wildfire smoke exposure increases *general* emergency room visits and hospitalization. While the existing literature on the health effects of wildfire pollution usually focuses on circulatory and respiratory related health care utilization, the consequences of pollution exposure can potentially extend beyond these diagnosis groups. Since we observe the primary diagnosis associated with each emergency room visit and hospital admission, in this subsection we examine utilization effects across a range of diagnosis groups.

In Table 6, we separately estimate the same-day utilization effects by primary diagnoses in both the emergency room setting and the hospitalization setting. We examine seven general diagnosis groups, including circulatory, respiratory, injury, digestive, neoplasm, infection, and genitourinary. We are first interested in whether and to what extent circulatory and respiratory related utilization explains the general emergency room visits and hospitalization findings. We start with column 1 and column 2. Our estimates suggest precise increases for both diagnoses, with stronger effects for circulatory diagnosis. For example, the two groups explain about 45 percent of the general hospitalization effect (Table 4, panel A, column 2). In column 3 and column 7, we report that the remaining effect is mainly explained by injury and urological diagnoses (including urinary tract infection and renal failure). Columns 4 to 6 suggest no consistent evidence of increases in utilization related to digestive, neoplasm, and infectious diseases.

In the Appendix, we further explore diagnoses sub-groups in circulatory, respiratory, injury, and genitourinary categories. We find evidence that increase in both ER and hospitalization in the circulatory category is to a large extent explained by diagnoses related to cerebrovascular events, ischemic heart disease, and heart failure. For respiratory, the increases are due mainly to lower respiratory tract infections. While exposure to wildfire smoke is unlikely to directly cause injury, it is plausible that pollution causes physical discomfort which in turn leads to distraction and occurrences of various accidents such as falls. Somewhat consistent with the view, we find no specific diagnoses that appear to drive the injury findings. Finally, we find that the genitourinary results are driven by two specific groups: urinary tract infection and renal failure. We find this evidence to be reassuring, as individuals with these diseases are likely to be of relatively poor health and be more sensitive to deterioration of air quality.

5. Heterogeneous Effects by Background Pollution Levels

An important aspect of the damage caused by pollution exposure involves understanding the shape of the dose-response relationship and whether how the marginal damage of pollution exposure varies with current pollution. We now turn to explore heterogeneous effects by the background level of pollution concentration. The research question we ask here is: when exposed to the *same* pollution shock, do areas with different average levels of pollution exhibit differential mortality responses? The answer to this question is important for both the understanding of the pollution-health relationship and for environmental standard making, as air pollution regulation often targets to reduce the average level of pollution. However, answering this question is difficult even if one considers quasi-experimental variation in air pollution. The intrinsic challenge here is that the background level of pollution is often shaped by the pollution variation in the first place. For instance, an area may have relatively lower level of background pollution simply because it benefited more from a policy change that permanently reduced industrial activities in the region. In this case, the policy change does not represent a homogeneous shock to areas with high versus low background pollution level.

Our study context provides a unique opportunity to investigate such heterogeneity because the movements of smoke plumes are driven by wind patterns and therefore whether or not a location is covered by smoke on a particular day is plausibly unrelated to local conditions, including local background pollution levels. Further, since wind blows the same smoke over long distances, the intensity of the pollution impact of smoke exposure is also plausibly unrelated to local conditions. Finally, since smoke exposure creates an occasional short-term increase in air pollution, it is unlikely to affect the average difference in air pollution levels across regions.

We begin by verifying that the appropriateness of our setting using ground-based pollution monitor data. We first categorize each county with $PM_{2.5}$ data for 2005-2013 into deciles in terms of their average daily $PM_{2.5}$ concentration over the period, ranging from an average of 6.3 ug/m^3 in the bottom decile to 13.7 ug/m^3 in the top decile. Figure 5, panel A shows average annual smoke days by background $PM_{2.5}$ deciles. Results indicate no evidence of a difference in the propensity of smoke exposure between high versus low pollution areas. Thus it does not appear to be the case that high background-pollution areas experience significantly more smoke days than low background-pollution areas.[15]

Next, we verify that the size of the $PM_{2.5}$ increase associated with smoke exposure is also unrelated to background pollution. These results are shown in Panel B of Figure 5. Figure 6, panel B shows that smoke exposure increases $PM_{2.5}$ by around 2.5 ug/m^3, which agrees with our earlier finding in Table 2, and, importantly, that there is no significant relationship between the magnitude of the pollution effect of smoke exposure and background pollution. The magnitude of the estimate for counties in the top decile does appear to be slightly smaller than other groups, although the difference is not statistically significant.

The above two steps provides supportive evidence that exposure to smoke causes the same increase in pollution regardless of background pollution, and therefore that smoke exposure provides a good setting in which to investigate the relationship between background pollution and the effect of pollution shocks. Panel C of Figure 6 plots the relationship between the mortality effect of smoke exposure and background pollution, which exhibits a clear downward trend. The linear estimate predicts that a 1 ug/m^3 increase in the background $PM_{2.5}$ decreases mortality effects of a smoke day by 0.212 death per million when the average smoke effect is 0.522 death per million. As can be seen in Panel C of Figure 5, the magnitude of this effect is important, suggesting large mortality effects in the cleanest areas, but almost zero effect in the dirtiest.

A natural question at this point is whether our background pollution measure is picking up some other variable that may be confounding the results. In particular, since poor areas are likely to be more polluted and exhibit higher mortality rates, one might wonder whether we are picking up a trend in poverty rather than in background pollution. Panel B of Table 3, presents regression results where we include interactions of background pollution with smoke exposure and the fraction of the ZIP code below 200 percent of the federal poverty line with smoke exposure. In regressions including both interactions, we find that the negative relationship between smoke-related mortality and background pollution is significantly

[15] To the extent that smoke causes transient increase in $PM_{2.5}$ concentration, there is scope for smoke frequency to be positively correlated with background pollution. In practice, we find smoke frequency is not explanatory of background pollution measured as long-term (8-year) average $PM_{2.5}$. In appendix, we report that our main conclusions in this section are not sensitive to alternative definitions of background pollution, e.g., using only $PM_{2.5}$ readings from non-fire seasons, or using $PM_{2.5}$ readings before the beginning point of our study period.

different from zero, while the coefficient on the smoke-by-poverty variable is small and not statistically significant. Thus, the interaction with respect to background $PM_{2.5}$ cannot be explained by the effect heterogeneity by income levels. We also find that the heterogeneity also holds in multi-day mortality regressions; in fact, the relative strength of this effect appears to grow larger as we expand the look-ahead window.

We explore heterogeneity in healthcare use related to baseline pollution and poverty in Panel B of Table 4. Despite the negative relationship between background pollution and smoke related mortality, we find no relationship between background pollution and healthcare use. Thus, it does not appear that the healthcare system plays a role in moderating the impact of smoke exposure on mortality in high-pollution places, at least on average.

Interesting results do appear when we consider the interaction between smoke related healthcare use and poverty, where we find a positive relationship: smoke in poor areas increases healthcare use more than in wealthier areas. Further, this effect is driven almost entirely by increased use of outpatient ER services in poorer areas after smoke exposure. Since this is not associated with a similar increase in mortality on in ER visits that result in admission, it suggests that outpatient ER visits are being used more in poor areas to provide routine care in less serious cases that otherwise might be provided by a visit to a primary care physician.

Of course, the heterogeneity analysis does not reveal the causal impact of background $PM_{2.5}$ level: areas with different levels of air pollution can be different in many observable and unobservable ways, such as the level of investments in public protection against pollution exposure. Nevertheless, our results may be informative for policy makers. For example, the national $PM_{2.5}$ standard is set by the EPA at a daily average of 12 ug/m^3. A disproportionate amount of resources are devoted by both the federal and the local governments to the protection of public health in counties where pollution level is above this standard. However, we show that, at least when exposed to *transient* pollution variations, there is no evidence that individuals living in highly-polluted counties experience significant mortality effects. While quantifying the benefits of reducing *average* level of pollution is beyond the scope of this study, our results do suggest that resources may be deployed more effectively by focusing on reducing pollution shocks in less-polluted areas.

7. Conclusion

This paper provides the first national-scale analysis of the causal relationship between wildfire smoke exposure. By combining satellite-based data on all wildfire smoke plumes affecting the US with healthcare data on the universe of Medicare beneficiaries over a 9 year period, we are able to examine this relationship in greater detail and with greater statistical precision than earlier work. We document, for the first time, a strong, positive direct link between smoke exposure and adult mortality and show that the mortality effect of smoke exposure grows over time, suggesting that the mortality results are not merely due to short term harvesting. We also find that smoke exposure increases hospitalizations (all-cause and for circulatory and respiratory causes), emergency room visits, and healthcare spending. Comparing the health-care cost of smoke exposure to the mortality cost, we find that in the short run health care costs are about one third as large as the mortality costs using conventional figures for the value of a statistical life year.

Although there have been a number of studies looking at the health effects of wildfire smoke exposure, as discussed in the introduction, the evidence in these studies has been inconsistent. This is true both within studies (e.g., finding hospitalization effects for some causes or subpopulations but not overall) and across studies, and despite the fact that the link between the pollutants generated by wildfires (e.g., particulate matter) and health is has been more clearly established. One of the major contributions of this paper is that we are able to study how a wide variety of smoke events affect the universe of Medicare beneficiaries. The result is that we find strong and consistent evidence across a variety of measures that smoke exposure negatively affects health.

The geographic and temporal detail and scope of our data allow us to examine several questions related to the intensity and duration of smoke exposure and health effects. We find that the effect of smoke does not appear to be cumulative, with the marginal effect of being exposed to smoke for an additional day increasing with the length of the smoke episode. On the other hand, comparing the impact of smoke exposure on areas that are generally polluted with areas that are generally not polluted, we find that the mortality impact of smoke exposure is larger in areas that are generally less polluted.

This result is potentially important for policy makers. Generally speaking, anti-pollution resources are tend to be targeted at more polluted areas. However, our results suggest that, if pollution shocks are generally more harmful in cleaner areas, these resources may be deployed more effectively by focusing on reducing pollution shocks in less-polluted areas.

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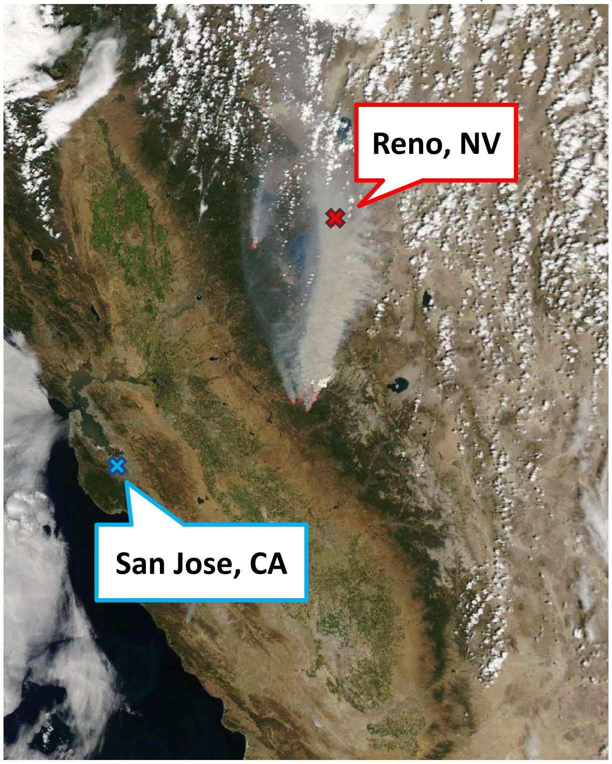
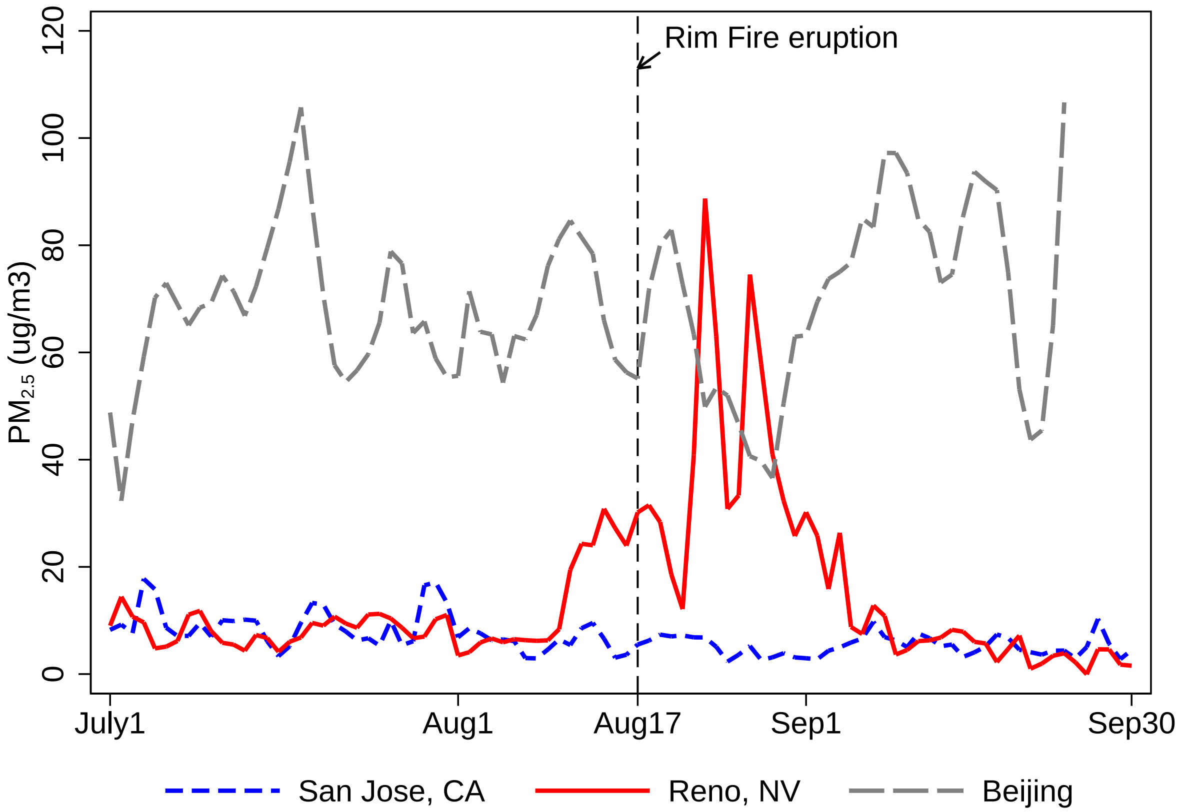
Figure 1: The Rim Fire (California 2013) and Air Pollution

Panel A. Satellite picture of the Rim fire (August 22, 2013)

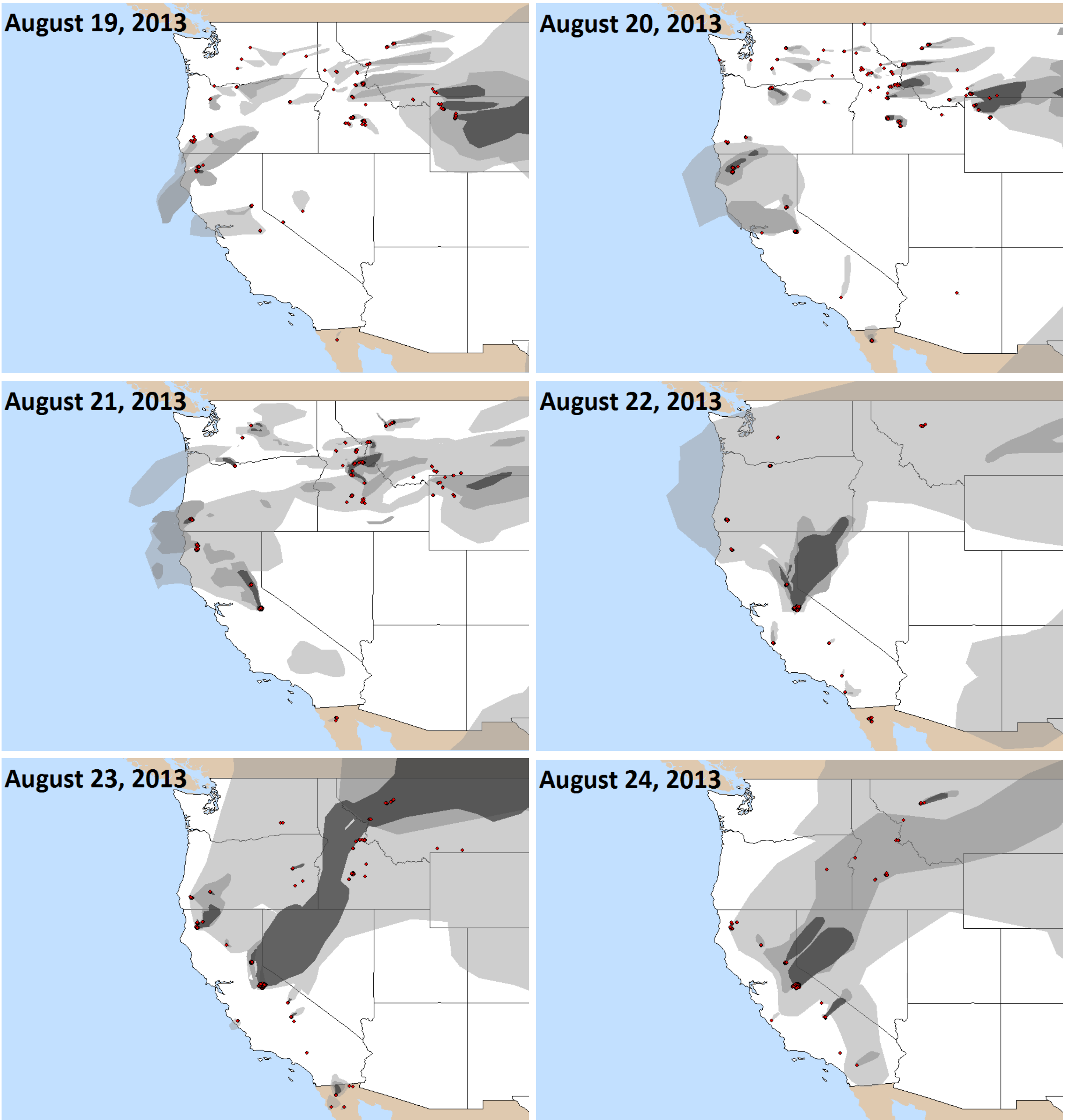


Panel B. $PM_{2.5}$ concentrations in San Jose, Reno, and Beijing



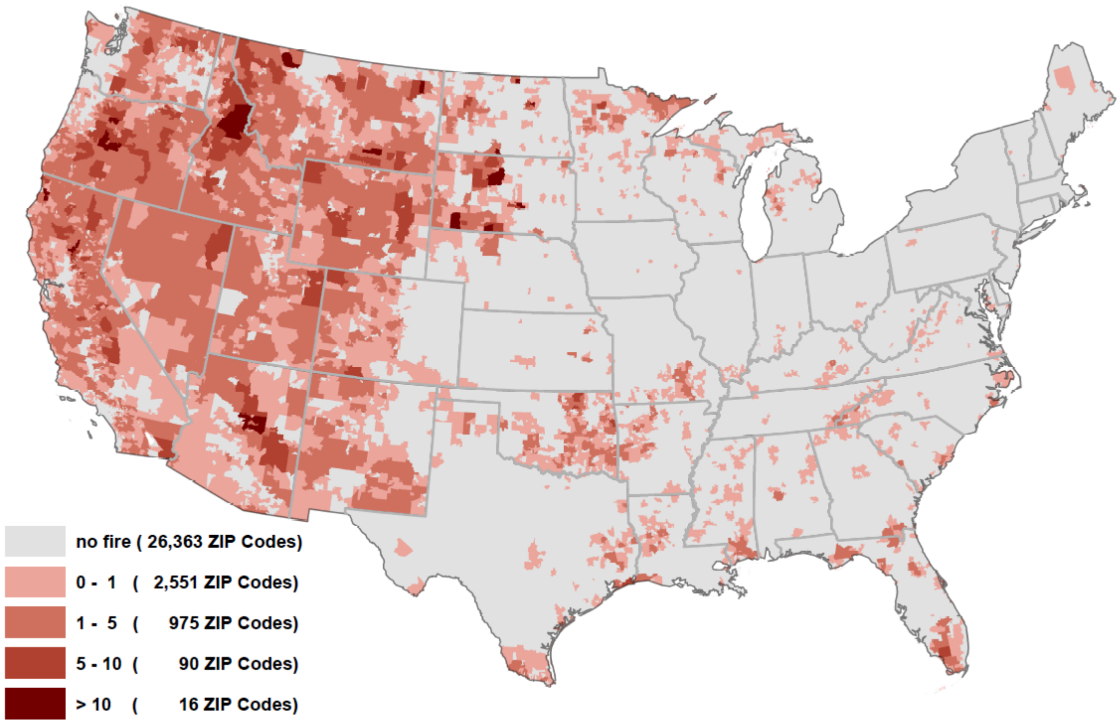
Notes: Panel A shows satellite picture of the Rim Fire (source: NASA Earth Observatory). Red cross highlights city of Reno, Nevada and blue cross highlights San Jose, California. Panel B shows daily $PM_{2.5}$ concentration in San Jose (ZIP code 95118) and Reno (ZIP code 89501). 5-day moving average $PM_{2.5}$ during the same time period is shown for Beijing, China (source: U.S Embassy Beijing Air Quality Monitor program).

Figure 2: Smoke Plume Dynamics of the Rim Fire

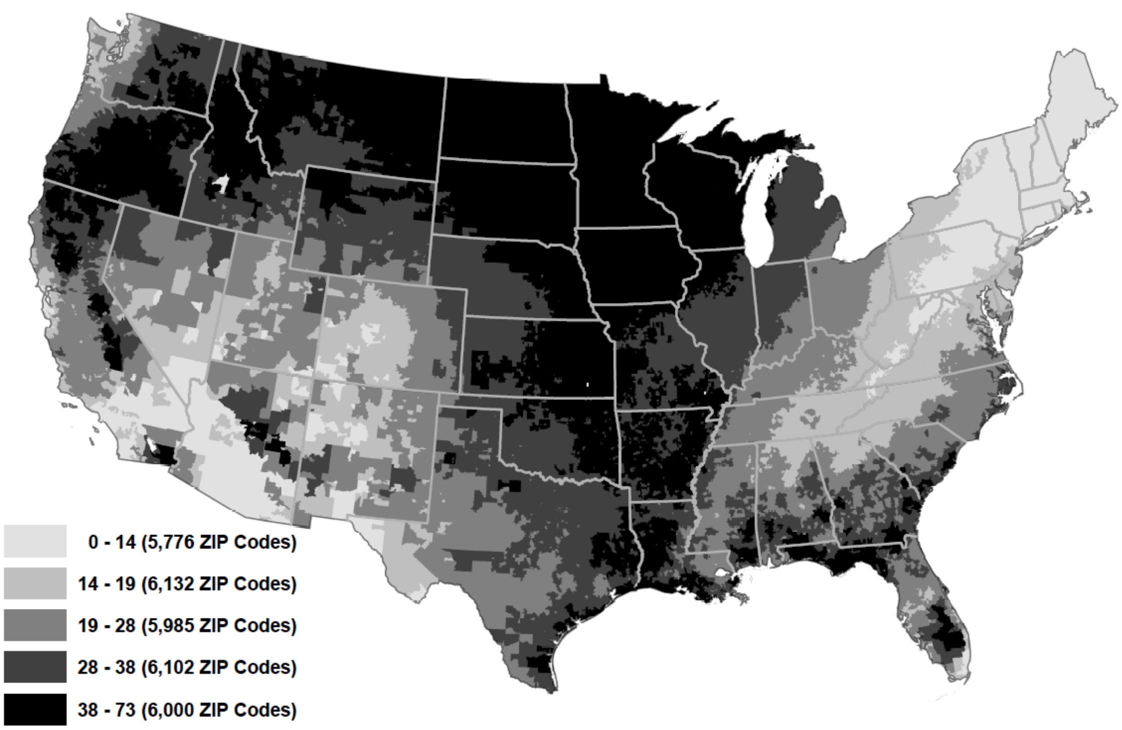


Notes: Graph show six daily snapshots of smoke plumes in the western US around Rim fire eruption. Polygon shapes represent smoke plumes. Red spots show places where MODIS satellite algorithm detects unusually warm surface temperatures associated with wildfires. Plume contours are presented to show relative thickness of the smoke plumes, although the density information does not represent actual ground level particulates concentration.

Figure 3: Average Wildfire and Smoke Exposure by ZIP Code, 2006-2012
Panel A. Annual number of wildfires



Panel B. Annual number of smoke days

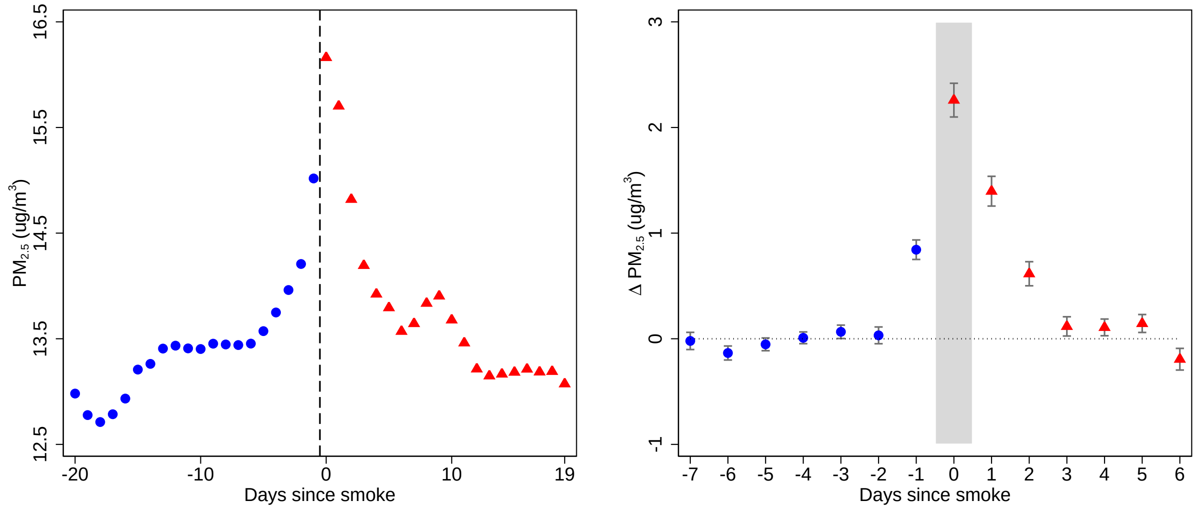


Notes: Panel A plots average annual number of wildfires using records from seven major wildland management agencies (Bureau of Indian Affairs, Bureau of Land Management, Bureau of Reclamation, California Department of Forestry and Fire Protection, National Park Service Fire and Aviation Management, US Fish & Wildlife Service, and Forest Service). Panel B plots average annual number of wildfire smoke exposure days.

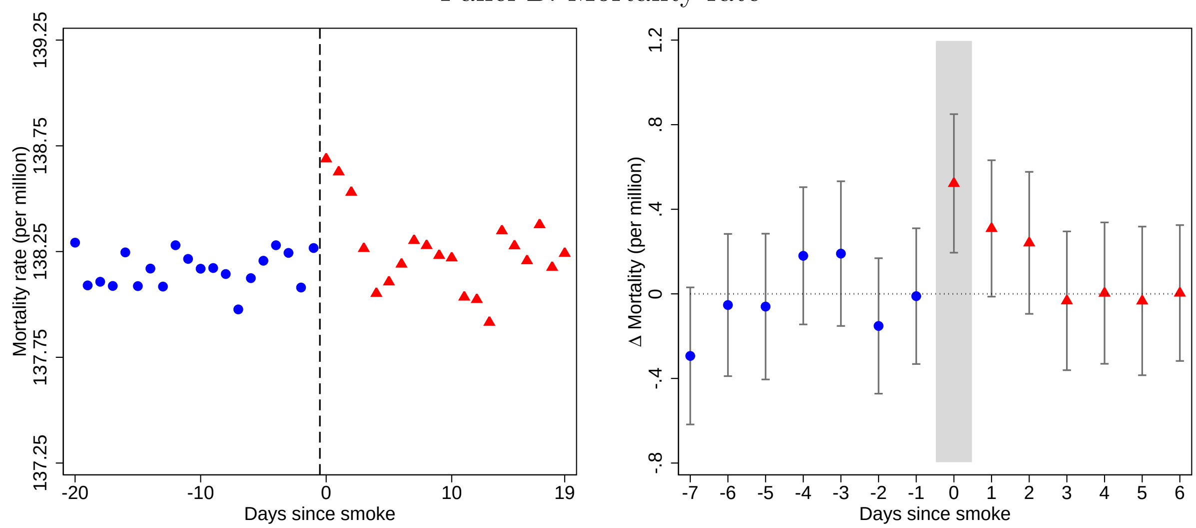
Figure 4: Event Study: Wildfire Smoke Exposure

L: Raw trend R: Leads & lags coefficients

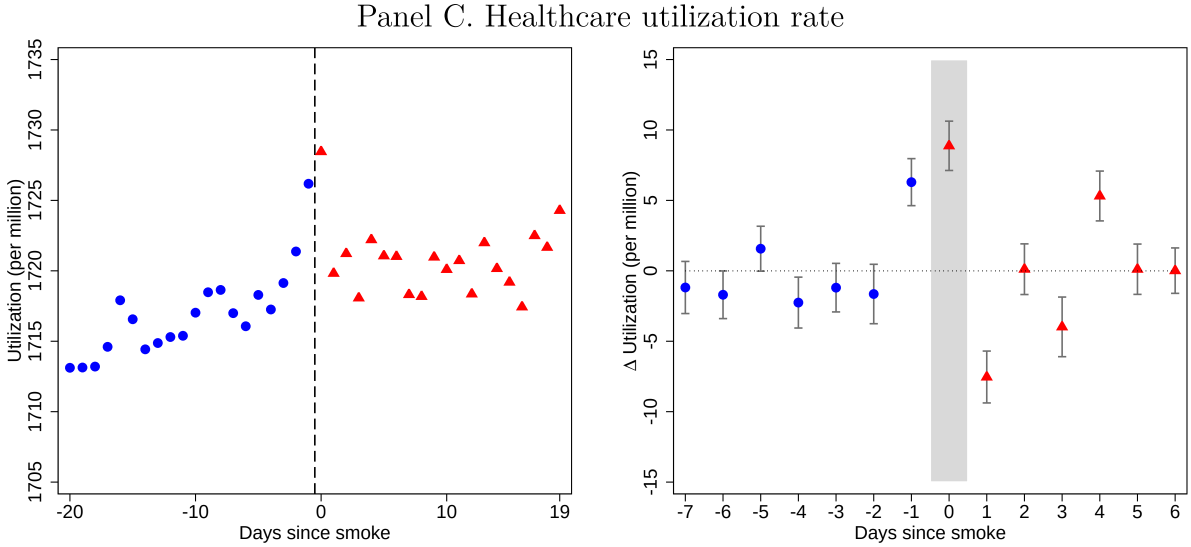
Panel A. $PM_{2.5}$ concentration



Panel B. Mortality rate

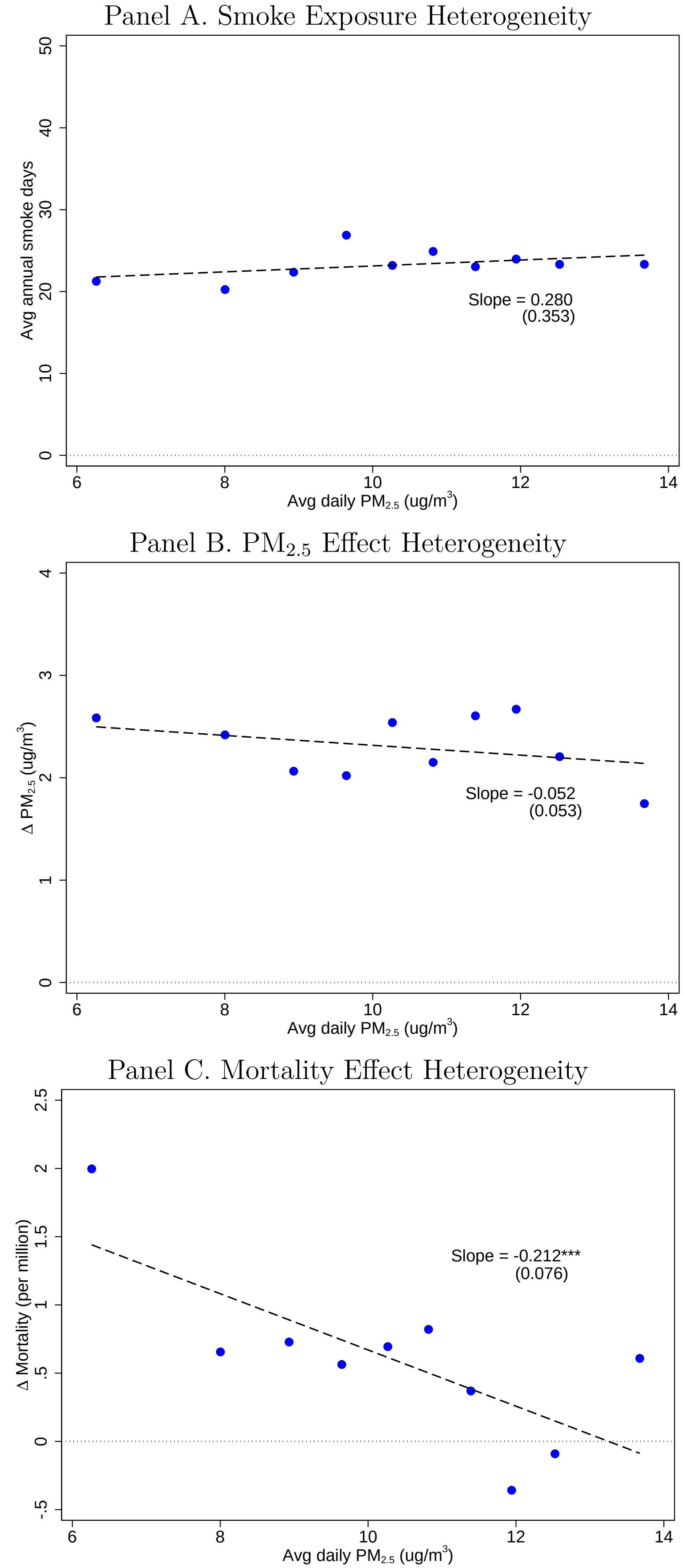


Panel C. Healthcare utilization rate



Notes: Left panels show mean outcomes within a 40-day window around the coded smoke day (event day = 0), controlling for day-of-year fixed effects and day-of-week fixed effects with no other controls. Right panels show baseline regression coefficients on 7 smoke leads, contemporaneous smoke, and 6 smoke lags. Bars show 95% confidence intervals constructed using standard errors clustered at the county level.

Figure 5: Heterogeneity by Average $PM_{2.5}$ Concentration



Notes: Figure plots heterogeneity by bins of county's decile average daily $PM_{2.5}$ concentration from 2005-2013. Mean $PM_{2.5}$ concentration ($\mu g/m^3$) is shown on the x-axis. Panel A plots average number of smoke exposure days by $PM_{2.5}$ deciles. Panel B plots heterogeneous $PM_{2.5}$ effects of a smoke day by $PM_{2.5}$ deciles. Panel C plots heterogeneous mortality effects of a smoke day by $PM_{2.5}$ deciles. In all panels, dots show coefficient for each decile. Dashed lines show the slope of the decile estimates, obtained from separate regressions where the dependent variable is a running measure of average daily $PM_{2.5}$ concentration rather than bins.

Table 1: Summary Statistics

	(1) Mean	(2) Std. dev.	(3) N (ZIP Codes)
Panel A. Wildfire & smoke			
Distance to wildfire, all days (miles)	879	593	29,995
Distance to wildfire, smoke days (miles)	383	414	29,982
Smoke exposure (%)	6.37	24.41	29,814
Panel B. Health & utilization, Medicare-eligible			
Number of beneficiaries	1,255	1,662	29,812
Mortality rate	125.58	316.36	29,812
Panel C. Health & utilization, Medicare Fee-for-service			
Number of beneficiaries	935	1,218	29,800
Mortality rate	131.96	375.03	29,800
Inpatient admissions rate	1,121.36	1165.13	29,800
Outpatient emergency room visit rate	842.79	1029.67	29,800
Inpatient spending	12,624,974	18,826,172	29,800
Outpatient spending	4,053,705	5,617,540	29,800

Notes: Statistics are computed over ZIP Code-daily observations. Except for number of beneficiaries, all statistics are weighted by number of living Medicare beneficiaries aged 65 and over. Rates are per million beneficiaries. Spending variables are dollar per million beneficiaries.

Table 2: Effects of Wildfire Smoke on Air Pollution

	(1) $PM_{2.5}$	(2) PM_{10}	(3) O_3	(4) CO	(5) NO_2	(6) SO_2
Unit of measure:	μg/m^3	μg/m^3	ppm	ppm	ppb	ppb
Clean Air Act standards:	35	150	0.070	9	53	75
1(Smoke)	2.257***	3.916***	0.0027***	0.015***	0.746***	0.200***
	(0.079)	(0.101)	(0.0001)	(0.001)	(0.051)	(0.016)
Mean dep. var.	10.69	23.39	0.027	0.401	13.07	2.13
Std. effect	0.310	0.228	0.246	0.067	0.084	0.056
F-stat	548.5	316.7	312.0	55.3	194.7	49.8
N	25,650,859	15,847,612	38,524,141	23,944,366	23,520,486	27,386,570
N (counties)	1,691	1,292	1,826	728	827	1,119

Notes: NAAQS standards are shown for $PM_{2.5}$ (24 hours), PM_{10} (24 hours), O_3 (8 hours), CO (8 hours), NO_2 (1 year), and SO_2 (1 hour). Regressions control for ZIP Code×week-of-year fixed effects, day-of-week fixed effects, state×year fixed effects, 3-day smoke leads and lags, 10-degree daily temperature bins, and quadratic daily precipitation. Standard errors are clustered at the county level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table 3: Effects of Wildfire Smoke on Mortality

	(1) $PM_{2.5}$ μg/m^3	(2) Mortality 1-day	(3) Mortality 3-day	(4) Mortality 7-day
Panel A. Average effects				
1(Smoke)	2.259***	0.522***	1.204***	1.434***
	(0.081)	(0.167)	(0.237)	(0.312)
Mean dep. var.	10.69	125.58	376.62	878.21
N	25,525,917	84,466,933	84,466,933	84,466,933
Panel B. Effects by general pollution and poverty characteristics				
1(Smoke) × Avg. $PM_{2.5}$	-0.065	-0.172**	-0.489***	-0.993***
	(0.058)	(0.077)	(0.168)	(0.315)
1(Smoke) × $\text{Poverty}_{200\%\ \text{FPL}}$	0.006*	0.005	0.041	0.080
	(0.003)	(0.013)	(0.167)	(0.049)
1(Smoke)	2.272***	0.601***	1.392***	2.069***
	(0.072)	(0.186)	(0.272)	(0.386)
N	25,033,137	61,807,795	61,807,795	61,807,795

Notes: Outcome variables are ZIP Code-daily pollution (column 1) and mortality rates in the next k-day window, where $k = 1, 3, 7$ as indicated by column names (column 2 - 4). Regressions control for ZIP Code×week-of-year fixed effects, day-of-week fixed effects, state×year fixed effects, 7 smoke leads and 6 smoke lags, 10-degree daily temperature bins, and quadratic daily precipitation. Both "Avg. $PM_{2.5}$" (ug/m3) and "$\text{Poverty}_{200\%\ \text{FPL}}$" (percent) are de-meaned. Standard errors are clustered at the county level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table 4: Effects of Wildfire Smoke on Healthcare Utilization

	(1) General utilization	(2) Inpatient admissions	(3) Outpatient ER visits
Panel A. Average effects			
1(Smoke)	9.282***	5.892***	3.390***
	(0.901)	(0.692)	(0.534)
Mean dep. var.	1,964.35	1,121.36	842.79
N	84,435,934	84,435,934	84,435,934
Panel B. Effects by general pollution and poverty characteristics			
1(Smoke) $\times$ Avg. $PM_{2.5}$	0.364	0.576	-0.212
	(0.517)	(0.372)	(0.331)
1(Smoke) $\times$ $\text{Poverty}_{200\%\ \text{FPL}}$	0.363***	0.062	0.300***
	(0.080)	(0.061)	(0.055)
1(Smoke)	9.643***	5.490***	4.153***
	(1.074)	(0.813)	(0.644)
N	61,807,795	61,807,795	61,807,795

Notes: Regressions control for ZIP Code×week-of-year fixed effects, day-of-week fixed effects, state×year fixed effects, 7 smoke leads and 6 smoke lags, 10-degree daily temperature bins, and quadratic daily precipitation. Both "Avg. $PM_{2.5}$" (ug/m3) and "$\text{Poverty}_{200\%\ \text{FPL}}$" (percent) are de-meaned. Standard errors are clustered at the county level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table 5: Effects of Wildfire Smoke on Other Healthcare Utilization

	(1) General ER visits	(2) Inpatient spending	(3) Outpatient spending
1(Smoke)	5.774***	76,678***	113,617***
	(0.689)	(11,487)	(9,288)
Mean dep. var.	1,399.351	12,624,974	4,053,705
N	84,435,934	84,435,934	84,435,934

Notes: Outcome variables are ZIP Code-daily utilization as indicated by column names. In column 2 and 3, spendings are in $ per million FFS beneficiaries. Regressions control for ZIP Code×week-of-year fixed effects, day-of-week fixed effects, state×year fixed effects, 3-day smoke leads and lags, 10-degree daily temperature bins, and quadratic daily precipitation. Standard errors are clustered at the county level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table 6: Effects of Wildfire Smoke on Healthcare Utilization: Diagnosis-Specific Effects

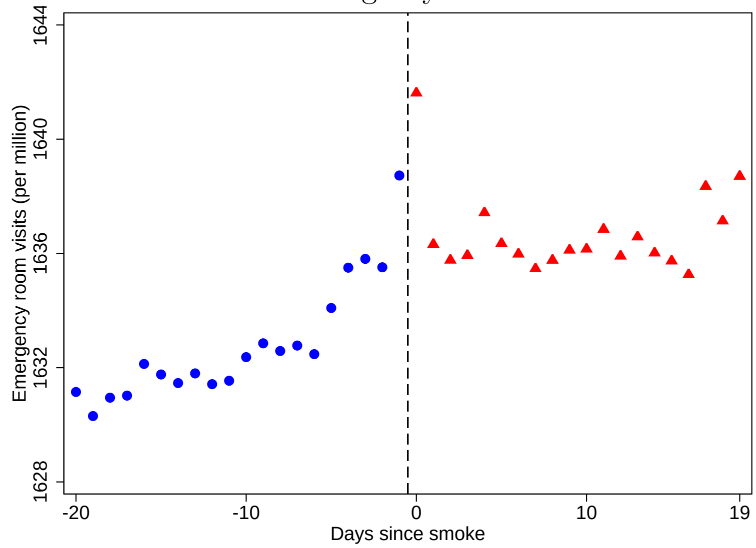
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Diagnosis:	Circ	Resp	Injury	Digest	Neop	Infect	Urology
Panel A. Dep. var. = emergency room visits (per million)							
1(Smoke)	1.131***	0.384*	2.028***	-0.189	0.069	0.156	0.668***
	(0.263)	(0.208)	(0.294)	(0.175)	(0.073)	(0.124)	(0.174)
Mean dep. var.	216.75	146.77	246.90	109.62	17.24	48.34	86.76
Panel B. Dep. var. = hospitalization rate (per million)							
1(Smoke)	1.805***	0.833***	0.494***	-0.067	0.267**	0.213	0.499***
	(0.290)	(0.203)	(0.162)	(0.160)	(0.121)	(0.131)	(0.154)
Mean dep. var.	260.51	133.66	94.97	93.45	47.70	49.99	67.84

Notes: Outcome variables are diagnosis-specific ZIP Code-daily emergency room visits (panel A) and hospitalization rate (panel B). ICD-9 codes used are circulatory (390-459), respiratory (460-519), injury (800-999), digestive (520-579), neoplasm (140-239), infection (001-139), and genitourinary (580-629). Regressions control for ZIP Code×week-of-year fixed effects, day-of-week fixed effects, state×year fixed effects, 3-day smoke leads and lags, 10-degree daily temperature bins, and quadratic daily precipitation. Standard errors are clustered at the county level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

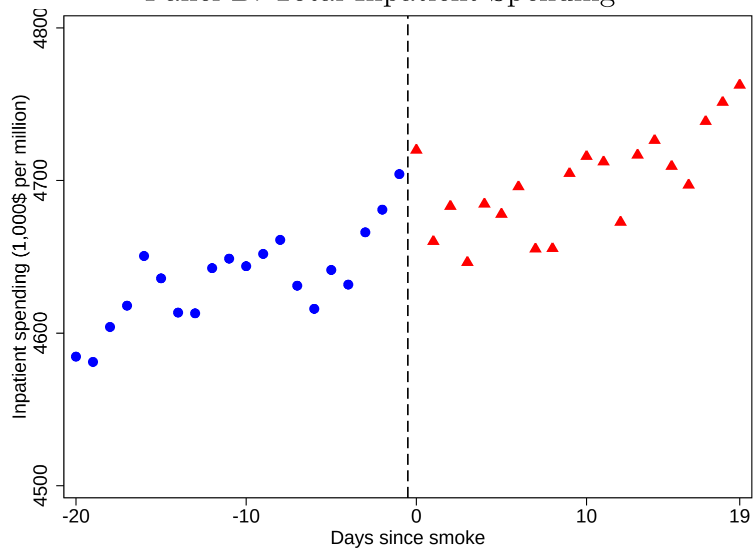
Additional Figures and Tables

Figure A.1: Trends: Other Health Care Utilization around Wildfire Smoke Exposure

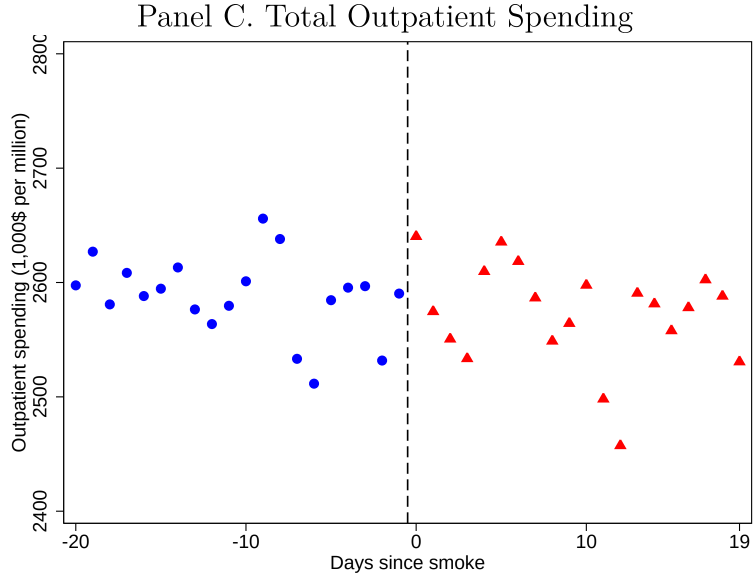
Panel A. Emergency room visits



Panel B. Total Inpatient Spending

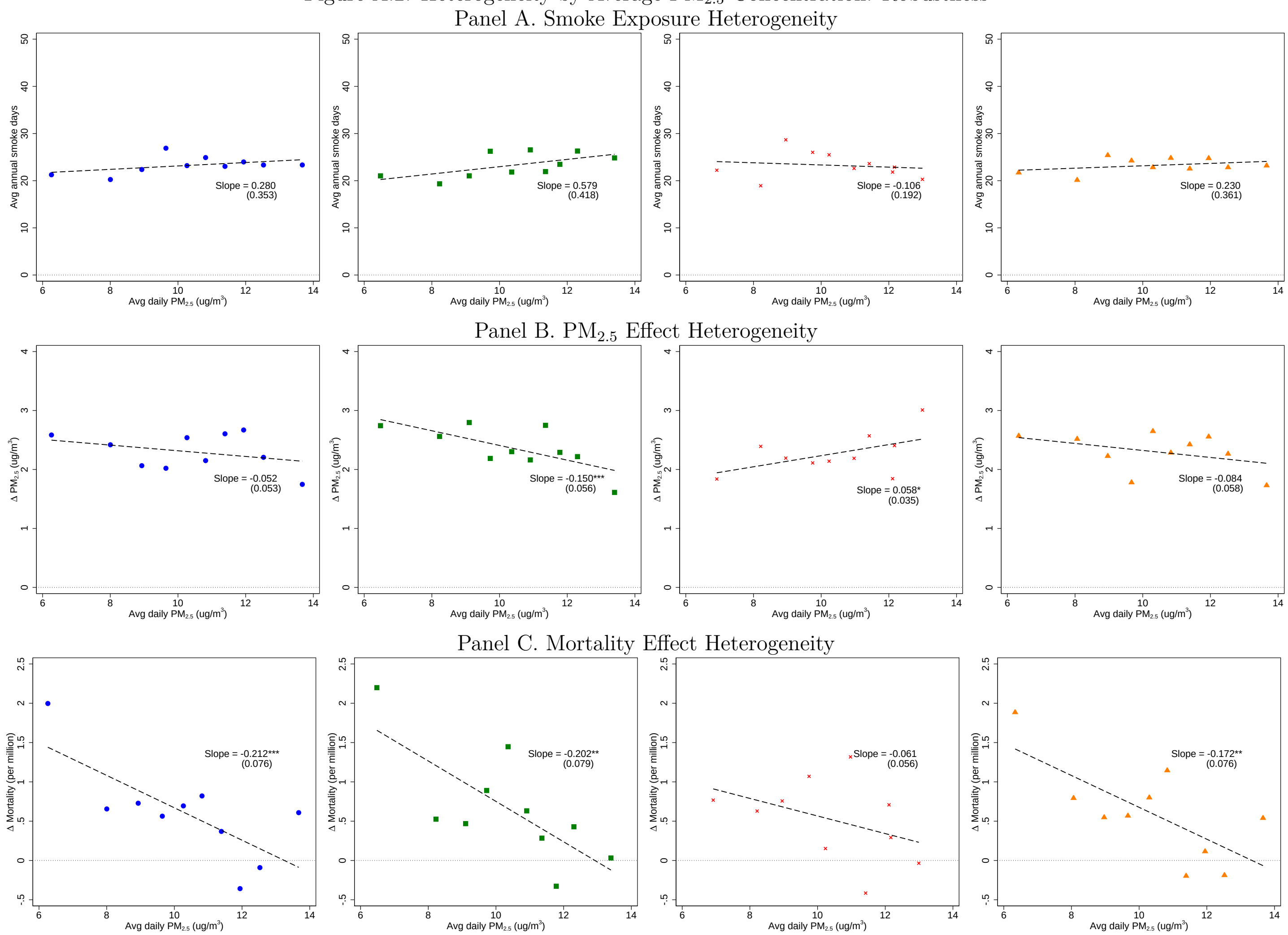


Panel C. Total Outpatient Spending



Notes: Figure presents mean daily utilization within a 40-day window around the coded smoke day (event day = 0). Sample includes all Medicare fee-for-service beneficiaries aged 65 and over. There are 6,511,390 smoke events at the ZIP Code-day level. Panel names indicate outcome variables. All regressions control for day-of-year fixed effects and day-of-week fixed effects with no other controls.

Figure A.2: Heterogeneity by Average $PM_{2.5}$ Concentration: Robustness



Notes: Average daily $PM_{2.5}$ concentration defined using all data (blue circles); excluding June - September data (green squares); June - September data (red crosses); excluding smoke ZIP Code×days (orange triangles)

Table A.1: Specification Checks: Alternative Fixed Effects Strategies

Indep. var. = *Smoke*	(1)	(2)	(3)	(4)	(5)	(6)
$PM_{2.5}$ (ug/m^3)	2.213***	2.300***	2.245***	2.336***	2.185***	2.262***
	(0.076)	(0.078)	(0.075)	(0.073)	(0.084)	(0.082)
Same-day mortality (per million)	0.400**	0.282	0.520***	0.451**	0.512***	0.474**
	(0.167)	(0.178)	(0.167)	(0.180)	(0.193)	(0.195)
Same-day inpatient$ (per million FFS)	65,796***	22,299*	69,507***	24,081*	68,794***	25,496*
	(12,581)	(12,517)	(12,567)	(12,773)	(12,726)	(13,226)
Same-day outpatient$ (per million FFS)	113,068***	13,829**	120,561***	15,831***	117,006***	12,231**
	(9,467)	(5,599)	(9,378)	(5,710)	(7,846)	(5,903)
FE: ZIP	✓	✓				
FE: ZIP×wk-of-yr			✓	✓		
FE: ZIP×day-of-yr					✓	✓
FE: Yr	✓		✓		✓	
FE: Wk-of-yr	✓					
FE: Day-of-week	✓		✓		✓	
FE: Date		✓		✓		✓

Notes: Each column presents a different fixed effects strategies. All regressions control for 3-day smoke leads and lags, 10-degree daily temperature bins, and quadratic daily precipitation. Standard errors are clustered at the county level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table A.2: Specification Checks: Alternative Controls and Samples

Indep. var. = *Smoke*	(1) $PM_{2.5}$ (ug/m^3)	(2) Mortality (per mil)	(3) Inpatient$ (per mil FFS)	(4) Outpatient$ (per mil FFS)
A. Alternative smoke measure				
"Deep" smoke	2.392***	0.529***	85,816***	128,527***
	(0.081)	(0.183)	(13,325)	(10,691)
B. Alternative weather controls				
No weather ctrls.	2.667***	0.654***	86,428***	117,876***
	(0.087)	(0.163)	(11,332)	(8,700)
Temperature bins × states	2.182***	0.569***	77,252***	116,563***
	(0.071)	(0.164)	(11,278)	(9,106)
Wind direction bins × states	2.046***	0.463***	74,152***	114,497***
	(0.067)	(0.167)	(11,415)	(9,212)
C. Alternative smoke leads & lags				
No leads & lags	3.032***	0.635***	72,804***	132,429***
	(0.100)	(0.151)	(10,330)	(8,607)
7 leads & 7 lags	2.265***	0.510***	73,304***	117,005***
	(0.082)	(0.167)	(11,544)	(9,285)
20 leads & 20 lags	2.214***	0.468***	67,682***	121,189***
	(0.083)	(0.170)	(11,313)	(9,624)
D. Subsamples				
May to September only	2.295***	0.486***	72,080***	151,822***
	(0.087)	(0.184)	(12,444)	(9,600)
Western U.S. only	1.316***	0.890**	35,878	54,414**
	(0.113)	(0.382)	(25,906)	(26,623)
Eastern U.S. only	2.471***	0.460**	86,987***	126,208***
	(0.073)	(0.185)	(12,475)	(9,478)

Notes: Each row presents a different specification. As a baseline, all regressions control for 3-day smoke leads and lags, 10-degree daily temperature bins, and quadratic daily precipitation. "Deep smoke" indicates days when a ZIP Code is entirely covered by smoke plume. "Wind direction bins" is daily wind direction at the centroid of the ZIP Code's parent county, categorized into 60-degree bins. "May to September" is the usual wildfire season in our data. "Western U.S." refer to the states of Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, and Wyoming. "Eastern U.S." are lower 48 states except the western states. Standard errors are clustered at the county level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table A.3: Effects of Wildfire Smoke on Diagnosis-Specific Emergency Room Visits and Hospitalization: Cardiovascular and Respiratory Diagnoses

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Circulatory						Respiratory				
Diagnosis:	Ischemic heart disease	Heart rhythm disturbance	Heart failure	Cerebro-vascular events	Peripheral vascular disease	Others	COPD	URTI	LRTI	Asthma	Others
Panel A. Same-day emergency room visits (per million)											
Smoke	0.189**	0.031	0.184*	0.357***	0.041	0.330*	-0.051	-0.064*	0.477***	0.073	-0.051
	(0.085)	(0.029)	(0.110)	(0.109)	(0.039)	(0.175)	(0.107)	(0.035)	(0.120)	(0.046)	(0.100)
Mean dep. var.	23.93	2.15	45.60	38.95	4.90	101.3	42.83	4.25	53.33	8.78	37.35
Panel B. Same-day hospitalization rate (per million)											
Smoke	0.185**	0.036	0.296**	0.528***	0.069	0.690***	0.054	0.008	0.682***	0.031	0.058
	(0.093)	(0.034)	(0.123)	(0.116)	(0.070)	(0.189)	(0.094)	(0.009)	(0.128)	(0.037)	(0.108)
Mean dep. var.	27.33	2.94	55.92	46.29	14.61	114.36	34.01	0.288	54.32	6.12	39.13

COPD = Chronic obstructive pulmonary disease
URTI = Upper respiratory tract infections
LRTI = Lower respiratory tract infections

Notes: Outcome variables are diagnosis-specific ZIP Code-daily emergency room visits (panel A) and hospitalization rate (panel B). ICD-9 codes used are ischemic heart disease (410-414, 429), heart rhythm disturbance (426-427), heart failure (428), cerebrovascular events (430-438), peripheral vascular disease (440-449), COPD (490-492, 494, 496), URTI (460-465), LRTI (466, 480-487), and asthma (493). Regressions control for ZIP Code×week-of-year fixed effects, day-of-week fixed effects, state×year fixed effects, 3-day smoke leads and lags, 10-degree daily temperature bins, and quadratic daily precipitation. Standard errors are clustered at the county level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table A.4: Effects of Wildfire Smoke on Diagnosis-Specific Emergency Room Visits and Hospitalization: Injury and Genital Diagnoses

	(1)	(2)	(3)	(4)	(5)	(6)
	Injury			Genital		
Diagnosis:	Bone frac	Med complic	Othrs	UTI	Renal fail	Othrs
Panel A. Same-day emergency room visits (per million)						
Smoke	0.493***	0.007	1.528***	0.290**	0.288***	0.090
	(0.152)	(0.085)	(0.237)	(0.122)	(0.077)	(0.097)
Mean dep. var.	66.27	22.86	157.2	43.75	14.87	27.90
Panel B. Same-day hospitalization rate (per million)						
Smoke	0.166	0.164*	0.164**	0.151*	0.256***	0.093
	(0.119)	(0.091)	(0.075)	(0.091)	(0.084)	(0.082)
Mean dep. var.	48.68	28.36	18.19	27.12	18.57	22.28
UTI = Urinary tract infections						

Notes: Outcome variables are diagnosis-specific ZIP Code-daily emergency room visits (panel A) and hospitalization rate (panel B). ICD-9 codes used are bone fracture (800-829), medical care complication (996-999), urinary tract infection (5990), and renal failure (5849). Regressions control for ZIP Code×week-of-year fixed effects, day-of-week fixed effects, state×year fixed effects, 3-day smoke leads and lags, 10-degree daily temperature bins, and quadratic daily precipitation. Standard errors are clustered at the county level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.