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Behavior Mediates the Health Effects of Extreme Wildfire Smoke Events
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ABSTRACT

Air pollution is known to negatively affect a range of health outcomes. Wildfire smoke is an increasingly important contributor to air pollution, yet extreme smoke events are highly salient and could induce behavioral responses that alter health impacts. We combine geolocated data covering the near universe of 127 million emergency department (ED) visits in California with estimates of daily surface wildfire smoke PM2.5 concentrations and quantify how increasingly acute wildfire smoke events affect ED visits. Low or moderate levels of ambient smoke increase total visits by 1-1.5% in the week following exposure, but extreme smoke days reduce total visits by 6-9%, relative to a day with no smoke. Reductions persist for at least a month. Declines during extreme exposures are driven by diagnoses not thought to be acutely impacted by pollution, including accidental injuries, and come disproportionately from less insured populations. In contrast, health outcomes with the strongest physiological link to short-term air pollution increase dramatically: ED visits for asthma, COPD, and cough all increase by 30-110%in the week after one extreme smoke day. Because low and moderate smoke days vastly outweigh extreme smoke days in our sample, we estimate that smoke exposure was responsible for roughly 3,000 additional ED visits per year in CA from 2006-2017.

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Introduction

Extreme weather and air pollution events are known to negatively affect a broad range of health outcomes. For instance, there is a large body of evidence documenting increases in emergency department (ED) visits for cardiovascular and respiratory conditions, injuries, infections, and other conditions exacerbated by environmental stressors during or following heat waves,[1–5] hurricanes and other extreme weather,[6–8] and intense pollution events.[9–18] However, when environmental conditions are sufficiently hazardous, people may alter their behavior in response, and this avoidance behavior could shape health-seeking behaviors or health risks and, in turn, health outcomes. Previous work has documented that changes in health seeking behavior lead to fewer ED visits on snowy days and during hurricanes.[6,19–21] At the same time, people may also alter their behavior in ways that reduce certain health risks. For example, spending more time at home can reduce time spent driving and lead to fewer car accidents and thus fewer trauma hospitalizations.[22] Changes in ED visits, or any health outcome, following environmental stressors are then a potentially complex combination of "direct" impacts on health outcomes that cannot be avoided, and "indirect" impacts from the health or monetary costs that were incurred to avoid the exposure. Comprehensive assessment of the societal impacts of extreme environmental events that are likely to grow under future climate change,[23] requires an accurate accounting of both types of costs.

Here we focus on understanding health impacts of wildfire smoke, one of the fastest growing environmental health risk factors in the US and in many other countries. Wildfire smoke events represent an increasingly common hazard faced by populations across the United States. Recent estimates suggest that, over the past decade, the number of days with any smoke in the air has roughly doubled, the number of days with smoke fine particulate matter ($PM_{2.5}$) $> 50 \mu g m^{-3}$ has increased by a factor of 12, and the number of days with smoke $PM_{2.5} > 100 \mu g m^{-3}$ has increased by a factor of more than 60.[24] Growing evidence has begun to establish the negative health effects of these exposures, especially for respiratory health.[25]

At the same time, increasingly extreme wildfire events are also highly salient, inducing observable changes in health-seeking behavior, mobility, and health-protective investments.[26] As wildfire smoke events become more extreme, these behavioral changes could increasingly shape observed health outcomes. Here we focus on the impact of wildfire smoke exposure on visits to the ED. Individual decisions to visit the ED balance tradeoffs of the perceived benefits from a visit to the ED (which grow with more acute conditions such as severe asthma) and the costs, including the perceived cost of exposure to extreme smoke. We highlight three channels through which wildfire smoke could induce behavioral responses that alter the decision to visit the ED. First, behavioral responses could modify exposures. For example, people may remain indoors and turn on air purifiers, which is likely to ameliorate negative health impacts and reduce the number of ED visits for conditions exacerbated by air pollution.[27,28] Second, environmental conditions could impact decisions to seek care in the ED.[29] People may opt not to visit the ED because they prefer to stay home (or are encouraged to stay at home by public officials), which could reduce ED visits regardless of how health is impacted. Third, behavioral responses may affect the probability of an injury occurring, even if that injury is unrelated to air pollution. For example, when people remain home, there is less opportunity to get into a car accident[30] but potentially more opportunity to have a home accident injury.[31]

While behavioral changes are more likely on the heaviest smoke days, it is less clear how, or if, behavior will change in response to lower-intensity smoke exposures, which have also become increasingly common. There is some recent evidence that people respond to wildfire smoke even at low levels, with increases in internet searches for air quality information and decreases in physical mobility observable even at low and moderate smoke $PM_{2.5}$ concentrations.[26] However, it remains unknown whether these changes in behavior are also enough to meaningfully change exposures, injury risk, and/or treatment-seeking behavior among smoke-exposed populations. It also remains poorly understood the extent to which short-term, low-level smoke exposures have negative "direct" effects on health outcomes. This combined lack of information renders a comprehensive health impact assessment of wildfire smoke very difficult.

We combine data covering the near universe of ED visits in California from 2006-2017, representing 127 million individual visits to non-federal hospitals, with recently developed spatially resolved estimates of daily surface $PM_{2.5}$ concentrations from wildfire smoke. Over the study period, both the number (Fig 1a) and rate (Fig S1) of total ED visits has increased over time, though spatial patterns vary for different primary diagnoses across California (Fig S2). Wildfire smoke has also been steadily increasing with substantial year-to-year variation (Fig 1c). We aggregate our data to the zipcode-day level based on the patient's zipcode of residence. We then estimate the effect of wildfire smoke intensity on ED visit rates using a panel fixed effects estimator that exploits local temporal variation in both exposure and outcome. While average wildfire smoke exposure is related to a suite of characteristics that could plausibly be correlated with ED visit rates,[32] local-level variation in daily exposure is highly random, driven by idiosyncrasies in where and when fires start and how the wind blows on a given day. Panel estimators that exploit within-location variation over time – and which are commonly employed in related environmental settings – plausibly isolate the impact of variation in smoke exposure from other time-invariant and time-varying factors that could be correlated with both wildfire smoke exposure and ED visits. In addition to location and day-of-week fixed effects, our model includes month-of-year fixed effects to account for average seasonality in both ED visits (Fig S3) and wildfire smoke, and wildfire-season by year fixed effects to control flexibly for trends in both smoke and hospitalizations in fire- and non-fire seasons. Because both health impacts and the decision to seek treatment can occur well after the time of exposure, we include up to four weeks of daily lags in our models. To understand how ED visits respond to different intensities of exposure, we estimate ED visits as flexible non-linear functions of wildfire smoke $PM_{2.5}$, using both flexible polynomials and non-parametric binned models.

Our primary analysis examines how total (i.e., all-cause) ED visits respond to wildfire smoke events. To distinguish the health impacts of wildfire smoke from the impacts of being close to a fire, we estimate responses both for the full sample and for the sub-sample of zipcodes far from active fires that are still affected by wildfire smoke. To better disentangle direct physiologic responses to smoke from indirect impacts induced by behavioral changes, we then estimate cause-specific responses where ED visits are grouped by the principal diagnosis associated with each visit (based on International Classification of Disease groupings). We evaluate whether effects differ by age and by health insurance status.

We find that moderate smoke concentrations (days with average smoke $PM_{2.5}$ concentrations in the 5-15 $\mu g m^{-3}$ range) increase total ED visit rates, but extreme smoke concentrations (daily smoke concentrations $> 50 \mu g m^{-3}$) substantially decrease ED visits. Responses differ substantially by diagnosis: for most acute respiratory conditions, ED visits increase monotonically scale with wildfire smoke intensity, whereas for the most common diagnoses in the ED, including accidental injuries and stomach pain of unknown cause, visits decline at high smoke levels. We estimate that in the week following a day with 50 $\mu g m^{-3}$ of wildfire smoke (99th percentile exposure), ED visits for asthma increase 110%, while visits for accidental injuries decline by 19%. These competing effects have, to our knowledge, not been directly observed in the pollution-health literature, although short-term reductions in hospitalizations have been noted in the face of wildfire smoke[33] and during exposure to other environmental stressors such as hurricanes and snowstorms[6,19–21]

The overall net impact of wildfire smoke on ED visits is a combination of increasing visits on low-smoke-intensity days and declining visits on high-intensity days. Because low-intensity days vastly outnumber high-intensity days in our data, our estimates suggest that wildfire smoke in California increased total ED visits in every year of our sample, with an average increase of roughly 3000 additional annual ED visits. This estimated increase represents about a fifth as many excess ED visits as have been attributed to one of the worst heatwaves in state history (16,166).[5]

While precise quantitative statements about the welfare impact of wildfire smoke are challenging given existing data – e.g. we do not have data with which to price or value the avoidance behavior – qualitative analysis suggests overall welfare losses from smoke but perhaps ambiguous effects on very bad smoke days. Individuals derive many benefits from days with no smoke in the air, including less need to protect themselves with purifiers or masks, increased enjoyment of outdoor spaces, and relative ease in seeking medical care. However, seeking medical care can also create negative externalities, if individuals only pay a portion of the cost of their ED visit and if visits for non-urgent conditions – which can make up a substantial portion of total visits[34,35] – make treatment of urgent conditions more difficult. At low levels of smoke exposure, we find little obvious evidence of avoidance behavior and clear evidence of an increase in ED visits, relative to a day with no smoke; on these days, welfare effects are likely negative. On very smokey days, however, we see a decline in injuries and a reduction in treatment-seeking behavior for a range of non-urgent symptoms; we also see a substantial increase in respiratory-related visits. The net effect of these competing channels depends on the relative size of the harm from the increased respiratory visits and any long-term harm from medical treatment foregone, relative to the benefits of a less-crowded ED and a reduction in so-called 'inappropriate-use' ED visits. While it seems plausible that harms from the former outweigh benefits from the latter, further work is needed to precisely quantify these tradeoffs.

1 Data and empirical approach

1.1 Data

ED data Data on emergency department visits come from California's Department of Health Care Access and Information (HCAI) (known as the Office of Statewide Health Planning and Development (OSHPD) prior to 2021). Our sample of the Emergency Department patient visit level dataset covers all of the approximately 127 million ED visits that occurred in non-federal facilities in California between January 1, 2006 and December 31, 2017. It does not include visits to federally run hospitals such as the VA. A summary of total ED visits and visits by ICD grouping is shown in Fig 1a.

Each record within the data consists of a single visit, also referred to as an outpatient encounter. Reported ED encounters include only those patients who had face-to-face contact with a provider. If a patient left without being seen, the patient did not have a face-to-face encounter with a provider and therefore the ED encounter does not constitute a visit and thus is not included in the data.

The data do include patients that were admitted to the hospital through the emergency department but do not include visits to Urgent Care centers or other service outlets not classified as Emergency Departments. For each visit we observe the date of admission, patient characteristics (zipcode of residence, age at time of service, self-reported race, sex), primary diagnosis, up to 20 secondary diagnoses, and hospital identifier.

For the main analysis we calculated daily zipcode level rates by zipcode of residence for total ED visits and separately for ED visits by primary diagnosis ICD grouping. To calculate daily rates we divided the total zipcode count of visits in a given grouping on that service date by the zip code population from the ACS in that year (see below for additional details). USPS zipcodes were mapped to ZCTAs and ZCTAs with 0 population were omitted from our sample. In total, 2,710 unique zipcodes of residence appear in our data. After dropping out-of-state zipcodes and mapping to ZCTAs, we were left with 9,208,683 zipcode (now ZCTA) by day observations corresponding to 2,101 zipcodes and 4,383 days spanning Jan 1, 2006 through Dec 31, 2017.

In addition to all-age all-cause rates and all-age rates by primary diagnosis we also calculated all-cause rates by age group (0-4, 5-17, 18-34, 25-64, 65+). To calculate daily age-specific rates for all-cause ED visits we summed the number of visits by age group in each zip-day and then divided by the age-group specific populations derived from the ACS. We do not calculate diagnosis-specific rates by age-group because the number of visits within each diagnosis by age group bin are too small to be stable.

We calculated the distance traveled for each visit as the distance from the centroid of the patient's residential zip code to the centroid of the zip code where the ED was located. To identify ED closures we calculated the total number of visits per day at each ED and then assumed any ED with 0 visits on a given date was closed. Distance to nearest open ED was then calculated at the zip-day level as the distance from residential zipcode centroid to the centroid of the zip code where the nearest ED open on that date was located.

Each visit in our dataset is associated with a primary diagnosis, which corresponds to a single ICD code as well as up to 20 secondary diagnoses that each correspond to separate ICD codes. Over the course of our sample all Emergency Departments in California transitioned from ICD-9 to ICD-10 codes. The transition occurred at different times for different hospitals. The groupings used here are based on ICD-9 groupings that were then mapped to ICD-10 codes relying primarily on the Centers for Medicare & Medicaid Services General Equivalence Mappings.[36] However, for some outcomes there are no 1-to-1 mappings between ICD-9 and ICD-10. In these cases we assigned additional ICD-10 codes to match the ICD-9 categories used in effort to avoid discrete jumps in diagnosis-specific rates of ED visits across the ICD-9 to ICD-10 transition. The ICD-9 and ICD-10 codes corresponding to each grouping used in the analysis are listed in the Supplement. Note that our main finding that all-cause ED visits decline at high smoke levels does not rely on the patient's diagnosis and thus is not influenced by ICD code groupings.

To calculate ED visit rates, we divide zipcode-day visits by zip level population. Single year annual zipcode population estimates are not available, so we rely on the 5-year averages derived from the American Community Survey (ACS) with the middle year in the running 5-year period corresponding to the year of the ED visit. For example, we estimate 2012 population for a given zipcode as the 5-year average population corresponding to that zipcode from 2010-2014 derived from the ACS. In addition to time-varying zipcode populations, average all-age and age-group specific zipcode populations across the sample period were calculated and used as regression weights for the corresponding regressions.

Wildfire smoke Estimates of smoke exposures come recently released estimates of daily wildfire smoke $PM_{2.5}$ concentrations for 10x10km^2 grid cells across the contiguous United States. These daily wildfire-driven $PM_{2.5}$ concentrations were derived with a machine learning model that used a combination of ground, satellite, and reanalysis data sources as inputs and was trained on daily estimates of wildfire smoke $PM_{2.5}$ concentrations at EPA pollution monitors.[24] The model was optimized to predict within-location variation in smoke $PM_{2.5}$ over time which is important given our empirical approach relies on temporal rather than spatial variation in smoke exposures to estimate impacts. One limitation of the estimated smoke $PM_{2.5}$ concentrations is that there are no associated uncertainty estimates so we are unable to formally incorporate uncertainty in exposure measurement into our statistical models of impacts.

To assign exposures to each zipcode (ZCTA) day from 2006-2017 we calculated the population weighted average smoke $PM_{2.5}$ concentration across grid cells using population data from the Gridded Population of the World (GPW), v4.[37] A summary of the data is shown in Fig 1c-d. On average, zipcodes in our sample experienced 30.4 days with smoke per year. Among those smoke-days, nearly half were associated with low smoke $PM_{2.5}$ concentrations (0-5 $\mu g m^{-3}$). Another 38% of smoke-days were associated with moderate smoke $PM_{2.5}$ concentrations (5-25 $\mu g/m^{-3)}$ and 12% of smoke-days were associated with smoke $PM_{2.5}$ concentrations above 25 $\mu g m^{-3}$.

Additional covariates In some specifications, we include daily temperature and daily rainfall as covariates. Daily temperature and rainfall were derived from PRISM[38] which estimate daily min and max temperature and total rainfall for 1km^2 grid cells across the United States. Following the procedure used to process smoke $PM_{2.5}$ data, we calculated daily population weighted averages across grid cells to derive zipcode by day averages. Population weights were derived from using population data from the Gridded Population of the World (GPW), v4[37] by resampling populations to the PRISM grid and taking pop-weighted averages of daily temperature and rainfall at the zipcode by day level.

To assess whether our estimated impacts are in fact due to smoke exposure or due to proximity to fire itself, we estimate and control for zip code distance to active fires. Our estimates for distance to active fire come from previous work[32] and are calculated the distance from zipcode centroid to the center of the nearest active fire point cluster each day. Fire point clusters are spatially concentrated groups of pixels identified using remotely sensing data from MODIS as having ongoing burning on that day. The purpose of clustering identified fire pixels rather than using every individual pixel identified as having fire is to distinguish active wildfires from other events that looks similar in the MODIS fire data. See ref[32] for details on the clustering algorithm used to identify groups of pixels found to best represent active wildfires.

For heterogeneity analysis, we include additional demographic and socioeconomic data from ACS. Five year averages from the American Community Survey covering 2011-2015 were used to represent average community-level characteristics across our 2006-2017 sample. Zipcode level average insurance coverage rates and income were derived from ACS variable B27015: 'Health insurance coverage status and type by household income in the past 12 months'). This variable provides population counts by insurance status and income group. To derive population counts by health insurance coverage status we summed across income groups and to derive population counts by income group we summed across health insurance coverage status. Population counts were then used to derive population shares for each sub-group.

A similar approach was used to characterize the population not speaking English (ACS variable B06007: 'Place of birth by language spoken at home and ability to speak English in the United States'). This variable provides population counts for people who speak English "less than 'very well'" separately by the primary language spoken at home and origin (native/non-native). To estimate the share of the population that speaks English less than 'very well', sub-populations were summed across places of birth and languages spoken at home to derive the total number of people that "'speaks English less than 'very well'". These totals were then used to calculate proportion of the population

These zipcode level average community characteristics were used either to stratify regressions (in the case of health insurance) or merely in a descriptive manner to help characterize the populations stratified by health insurance coverage rates (language ability, income) as shown in Fig S12.

1.2 Empirical approach

We model daily zipcode ED visit rates as a function of wildfire smoke on the day-of-visit and on days leading up the ED visit. Specifically we estimate ED visit rates per 100,000 people (y) in zipcode z in county c on date d and day-of-week w as a function of wildfire smoke and controls.

$$y_{zcdw} = \sum_{l=0}^{L} \beta^l f(smoke_{zcw,d-l}) + \alpha X_{zcdw} + \delta_z + \theta_{cm} + \eta_{ys} + \omega_w + \varepsilon_{zcdw} \tag{1}$$

Fixed effects at the zipcode level account for time-invariant differences across space (δ_z), at the year by season level account for trends in exposure and outcomes over time (η_{ys}), at the county by month level account for regional seasonality in exposure and outcomes (θ_{cm}) and at the day-of-week level account for weekly cycles in ED visits (ω_w). The motivation for allowing time trends to vary separately by wildfire season (May - October) and non-wildfire season is that there is extreme seasonality in certain diagnoses such as respiratory infections (Fig S3) and the conditions that drive high rates of infection are likely to vary over time and may be (likely negatively) correlated with conditions that influence the intensity of the wildfire smoke season. By allowing the wildfire and non-wildfire trends to vary separately we account for trends in non-wildfire season conditions that are important drivers of winter-time conditions like influenza.

Effects are calculated from OLS regression estimates of Equation (1) with various non-linear functional forms for $f(smoke_{zcw,d-l})$ considered including binned specifications, splines, and higher order polynomials. Our main specification (shown in Fig 2) is a 4th degree polynomial with 7 lags (day of visit plus seven additional daily lags for a total of eight terms per coefficient), i.e.:

$$f(smoke_{zcw,d-l}) = \sum_{l=0}^{7} \left(\beta_{1,l} smoke_{zcw,d-l} + \beta_{2,l} smoke^2_{zcw,d-l} + \beta_{3,l} smoke^3_{zcw,d-l} + \beta_{4,l} smoke^4_{zcw,d-l}\right) \tag{2}$$

To derive the cumulative response of wildfire smoke, we sum the coefficients for each polynomial degree across the day of visit and 7 additional lags. For example, β_1 is estimated as $\sum_0^7 \beta_{1,l}$, β_2 is estimated as $\sum_0^7 \beta_{2,l}$, and so on. The interpretation of the cumulative effect at, for example, a smoke $PM_{2.5}$ concentration of 25 μgm^{-3} is the effect of a day of smoke $PM_2.5$ at 25 μgm^{-3} on the total number of additional ED visits in the following 8 days (day of smoke plus seven additional days) relative to a day with no smoke $PM_{2.5}$. Confidence intervals for the polynomial specification shown in Fig 2a are derived by bootstrapping the equation 1,000 times where we sample zipcodes with replacement with probability proportional to their population.

The decomposition by diagnosis shown in Fig 2b is derived using the same approach described above but from separate regressions for each of the 14 diagnoses. For each smoke $PM_{2.5}$ concentration responses for individual diagnoses are then divided into positive or negative effects, sorted by magnitude, and plotted on top of each other. To account for multiple hypothesis testing we apply the Bonferroni correction to diagnosis specific associations. For example, because we analyze 14 different primary ICD groupings, the estimated 95% confidence intervals for for diagnosis specific associations (Fig S6) correspond to $\alpha = 0.05/14$.

We also estimate a binned version of Eq 1 by dividing daily smoke $PM_{2.5}$ concentrations into discrete bins and then estimating separate coefficients for each bin. This binned specification takes the form:

$$\begin{aligned} y_{zcdw} = &\sum_{l=0}^{7} \left(\sum_{b=1}^{B} \beta_{1,l} smokeBIN^b_{zcw,d-l} \right) \\ &+ \alpha X_{zcdw} + \delta_z + \theta_{cm} + \eta_{ys} + \omega_w + \varepsilon_{zcdw} \end{aligned} \tag{3}$$

where $smokeBIN^b_{zcw,d-l}$ is a dummy for whether smoke $PM_{2.5}$ in zip z and county c on day of week w and date $d - l$ falls into the range of bin b. The main binned specification divides smoke $PM_{2.5}$ concentrations into five bins corresponding to smoke $PM_{2.5}$ ranges of 0-5 (not inclusive of 0), 5-10, 10-25, 25-50, and > 50 μgm^{-3}. These cutoffs were selected to correspond to approximately the 50th, 75th, 90th, 95th, and 99th percentile of the smoke $PM_{2.5}$ distribution (Fig 1d). Additional versions of equation (3) are also estimated by alternatively dividing smoke $PM_{2.5}$ into 6 equally spaced 10 μgm^{-3} bins (0-10, 10-20, 20-30, 30-40, 40-50, >50) or by dividing smoke $PM_{2.5}$ into equally spaced 25 μgm^{-3} bins (0-25, 25-50, > 50). Results for all versions of the binned specifications are shown in Fig S4a. To derive the cumulative response across multiple days for the binned models we sum the coefficients for each bin across all lags.

Quantifying heterogeneity For cause- and age-specific regressions, we estimate Eq 3 separately for each ED visit rate. For cause-specific analysis, we evaluate the hypothesis that wildfire smoke increases ED visits for a given cause across numerous outcomes. To account for these multiple hypotheses we implement a Boneforroni correction to calculate adjusted 95% confidence intervals corresponding to Eq 3. Namely, we first estimate the standard errors for the sum of each bin's coefficients across lags (clustered at the zipcode level) and then we use these standard errors to calculate confidence intervals with $\alpha = \frac{0.5}{n}$ where n reflect the number of outcomes. We then refer to the confidence intervals as Bonferroni-adjusted 95% confidence intervals. For example, the 95% confidence intervals shown in Fig S6 are calculated as $\hat{\beta} \pm \Phi(0.025/14) * \hat{se}$.

Because we do not observe insurance status at the individual level, we cannot calculate ED visit rates specific to the insured (or uninsured) population. Instead, we divide zipcodes into terciles based on the average percentage of the population that has health insurance during our sample as reported in the American Community Survey. We then estimate Eq 3 separately for each subset of zipcodes. This approach allows us to estimate separate responses by insurance coverage status. However, average health insurance coverage rates are correlated with a suite of other factors (Fig S12) that we cannot empirically disentangle. Thus, we interpret the stratification by insurance coverage as a measure of vulnerability that includes insurance coverage and correlated factors.

Estimating ED Visits Attributable to Ambient Wildfire Smoke To estimate the number of ED visits attributable to wildfire smoke, we utilize the response curve shown in Fig 2 which corresponds to a regression estimate of Equation 2 and multiply $\beta_1 - \beta_4$ by observed smoke $PM_{2.5}$ estimates for each zipcode-day. Evaluating the estimated coefficients at observed smoke $PM_{2.5}$ levels produces estimates of the change in all-cause ED visit rates for each zipcode and day. We then scale these estimated rate changes by the population in each zipcode at the time and sum across zipcodes and days in each year. The output of this calculation is an annual estimate of additional ED visits statewide encompassing visits in the 7 days following every observed event 2006-2017. To estimate 95% confidence intervals on estimated attributable ED visits we follow the same bootstrapping procedure (described above) that was used to estimate confidence intervals on the response curve shown in Fig 2. Results of this estimation are shown in Fig S13.

2 Results

We find that total (all-cause) ED visit rates increase in response to low or moderate intensity wildfire smoke but decline in response to heavy smoke (Fig 2a). We estimate the largest positive effects on total ED visits when wildfire smoke $PM_{2.5}$ is in the 5-15 $\mu g m^{-3}$ range (for context average non-smoke $PM_{2.5}$ in California is 9 $\mu g m^{-3}$ and the EPA 24-hour standard for total $PM_{2.5}$ is 35 $\mu g m^{-3}$). At this intensity, total ED visits increase by an average of 0.9 additional daily visits per 100,000 (95% CI: 0.6-1.2) in the week following wildfire smoke. This change represents a 1.1% increase over the sample baseline rate of 75.3 ED visits per 100,000. We find that the response of total ED visits to wildfire smoke peaks at 10 $\mu g m^{-3}$ of smoke $PM_{2.5}$ (88th percentile in our data) and declines thereafter becoming negative for smoke $PM_{2.5}$ $>$20 $\mu g m^{-3}$ (95th percentile smoke intensity). At smoke $PM_{2.5}$ = 50 $\mu g m^{-3}$ (99th percentile) we estimate that total ED visits are lower by 7.3 visits per 100,000 (95% CI: 5.6-9.1) relative to a day in the same zipcode without wildfire smoke, a 9.8% decline in ED visits. The shape of the all-cause ED visits response is remarkably robust to modeling choices with respect to functional form, lag structure, fixed effects, controls, and weighting schemes (Fig S4).

The observed dose-response of total ED visits to wildfire smoke is the net of diagnosis-specific increases and decreases. Both the magnitude of the diagnosis-specific responses and the baseline frequency of visits for that diagnosis influence each diagnosis's contribution to the overall response. Fig S5 shows the frequency of ED diagnoses across our entire sample. The most common reasons people visit the ED in our sample include accidental injuries, symptoms such as cough or stomach pain of unknown cause, and respiratory conditions including respiratory tract infections (RTI) and asthma.

We find that responses of ED visits to wildfire smoke different substantially by diagnosis (Fig 2b, Fig S6). For most acute respiratory conditions we find increasing ED visits that monotonically scale with wildfire smoke intensity (Fig S7). The strongest responses are observed for asthma, COPD, and respiratory symptoms without a specific diagnosis (e.g., shortness of breath, cough), all of which increase by more than 30% in the week after an extreme smoke day, relative to a day without smoke (Fig 3). In contrast, for the most common diagnoses in the ED, most of which are not thought to be directly exacerbated by pollution exposure, visits decline at increasingly extreme smoke exposures; these declines more than offset respiratory increases and lead to an overall decline in total ED visits at extreme daily smoke concentrations. This is true even after limiting our sample to zipcodes far from active fires and controlling for ED closures, suggesting that the observed changes are driven by individual-level responses to smoke (Fig S4) and not individual responses to nearby fires or changes in the supply of available care. Results are also robust to including up to a month of lags of our smoke variable, reducing the likelihood that an extreme smoke day is simply displacing non-smoke-related visits to a later day. Our results for ED visits with principal diagnoses related to the circulatory system have wide confidence intervals and we observe no clear response of ED visits for these causes to wildfire smoke (Fig 3).

In absolute terms, the most common ED visit diagnoses see the largest declines in response to heavy wildfire smoke. However, the relative contribution of different diagnoses varied by smoke intensity (Fig S8). This pattern is seen both in aggregate and on a smaller scale within the most frequent principal diagnosis category, 'symptoms'. Within this diagnosis grouping, ED visits for non-respiratory symptoms like abdominal pain or digestive discomfort decline in response to smoke while ED visits for respiratory related symptoms (classified as symptoms because they are not diagnosed to have a specific cause like asthma or COPD), including cough and shortness of breath, increase with wildfire smoke intensity (Figs 3 and Fig S9). At lower smoke intensities the increases in visits for respiratory symptoms generate an increase in the overall symptoms category, but as smoke intensity increases the decline in visits for non-respiratory symptoms dominates. As a result, fewer visits for issues like stomach pain become a large part of the decline in ED visits for symptoms, and in turn, total ED visits.

The largest contributor to the estimated decline in total ED visits at high wildfire smoke intensities is fewer visits for accidental injuries (Fig S8), with declines observed for several different types of injuries (Fig S10) including both more urgent (fractures) and less-urgent (superficial injuries) conditions (Fig 3). We estimate that in the week following a day with 50 $\mu g m^{-3}$ of wildfire smoke (99th percentile exposure), ED visits for accidental injuries decline by 19% (95% CI: 9-30%) with visits for sprains, contusions, fractures, wounds and superficial injuries each estimated to decline by 15-25%.

Responses also differ by age and by health insurance coverage, both of which influence baseline ED utilization (young children and uninsured populations visit the ED at relatively higher rates in our data - see Fig S11 and Fig S12c). While the increases in total ED visits in response to low and moderate smoke levels are driven largely by additional visits for children under 5, the reduction in ED visits at high smoke intensities is driven primarily by reductions in visits among adults 18-64 and, to a lesser extent, people over 65 (Fig S11). We find that the reduction in ED visits for diagnoses that drive the observed decline at high smoke intensities, such as accidental injuries and general symptoms, are largest in the least-insured zipcodes. For example, we estimate that among less insured populations, ED visits for symptoms strongly decline in response to high intensity wildfire smoke while populations with high levels of insurance coverage exhibit no changes (Fig 4a). In contrast, for diagnoses with the most clear physiological linkages to wildfire smoke like asthma, we find that ED visits increase similarly across groups regardless of zipcode-level insurance coverage (Fig 4b).

The overall net impact of wildfire smoke on ED visits is a combination of increasing visits on low-smoke-intensity days and declining visits on high-intensity days. Because low-intensity days vastly outnumber high-intensity days in our sample (see histograms, Fig 2), our estimates suggest that wildfire smoke in California increased total ED visits in every year of our sample (Fig S13). Estimated annual increases attributable to wildfire smoke range from a low of 975 additional visits in 2010 (95% CI: 727-1,270) to a high of 6,195 additional visits in 2016 (95% CI: 2,566-8,615). On average across our sample, we estimate that wildfire smoke is responsible for 3,010 additional annual ED visits across California (95% CI: 1,760-4,380).

Discussion

Our results are broadly consistent with previous findings that ED visits for acute respiratory conditions increase following exposure to wildfire smoke.[9–18] In addition, we find evidence that ED visits for other conditions including general symptoms increase under low or moderate intensities of wildfire smoke. Collectively these impacts lead to increasing effects on total ED visits in the week following low or moderate exposure. However, when ambient wildfire smoke concentrations exceed 20 $\mu g/m^3$ (95th percentile smoke intensity in our sample), we find ED visit rates actually decline for many causes not typically directly linked to air pollution exposure, such as accidental injuries, abdominal pain, and digestive discomfort. While directly impacted conditions like respiratory symptoms steadily increase at higher wildfire intensities, these ailments represent a small fraction of total ED visits. For example, respiratory and cardiovascular diagnoses combined account for less than 1 in 5 principal diagnoses in our sample and thus any increases in the rates of these diagnoses at high smoke intensities are dominated by the accompanying decreases in more common outcomes resulting in a net decline in total ED visits. These competing effects have, to our knowledge, not been directly investigated in the pollution-health literature, although short-term reductions in hospitalizations have been noted in the face of wildfire smoke[33] and during exposure to other environmental stressors such as hurricanes and snowstorms[6, 19–21]

There are several potential mechanisms that could lead to fewer ED visits under extreme pollution conditions, including individuals being less likely to seek care, individuals changing their behavior in ways that alter their pollution exposure and/or alter their risk for non-pollution-related injury, or interruptions in the "supply" of care if individuals who are proximate to fires cannot access care due to emergency department closures. We find limited evidence that proximity to fire amplified the response of ED visits to smoke, suggesting that alterations to the supply of medical services are unlikely to be driving our results. Similarly, we do not find strong evidence that behavioral changes are effectively limiting smoke exposures: ED visits for respiratory conditions increase steadily as ambient smoke concentrations worsen. This increase is consistent with earlier findings of substantial infiltration of wildfire smoke into indoor residential environments,[26] suggesting that staying at home is not sufficiently protective to avoid health impacts.

Our findings do suggest that alterations to health-seeking behavior and behaviorally-induced changes in risks for non-pollution-related injury are critical determinants of smoke impacts. ED visits for superficial injuries and non-acute symptoms decline following intense wildfire smoke and do not rebound over the next month, suggesting individuals are often foregoing treatment for non-urgent conditions. Similarly, ED visits for fractures, traumatic injuries, and other severe injuries also decline following heavy smoke days and do not rebound, suggesting that reduced opportunity for injury also plays an important role. These findings are consistent with earlier evidence that found that on days with wildfire smoke $PM_{2.5} > 50\mu gm^{-3}$, the number of people who never leave their homes increases by approximately 10%.[26] The share of people who leave home briefly but still remain home for a higher than normal portion of the day is likely to be even higher.

Available evidence regarding which age groups are most vulnerable to respiratory impacts from wildfire smoke is mixed.[25] Consistent with our hypothesis that responses are strongest among sub-groups that utilize the ED more frequently, our age-specific results suggest that children under 5 comprise the largest portion of observed increases in ED visits following smoke exposure. Our results of similar magnitude increases in ED visits for asthma but differential decreases in ED visits for symptoms and injuries across insurance terciles suggests that while population-wide health, particularly among children, is negatively impacted by wildfire smoke, the overall decline in ED visits at high smoke intensities is driven at least in part by changes in behaviors among vulnerable populations for whom the ED may play a more prominent role as a healthcare service provider. While we focus here on insurance coverage, which may directly influence ED utilization (share of population with insurance coverage is negatively correlated with ED visit rates in our data), this measure is also highly correlated with other factors that might influence the relationship between wildfire smoke and ED visit rates including income, share of population that speaks English less than 'very well', and frequency of ED visits and we are not able to disentangle the effects of being insured from other co-varying factors (Fig S12).

Despite the declines in ED visits at high smoke intensities, we find that wildfire smoke increases total ED visits overall. Our estimated response curve indicates that total ED visits increase following exposure to wildfire smoke $PM_{2.5} \leq 20\ \mu gm^{-3}$ but decline in response to higher smoke intensities. However, only 5% of smoke-days have smoke $PM_{2.5} > 20 \mu gm^{-3}$. Given there are more than 10 million ED visits per year in California, smoke induced ED visits represent a small fraction of total ED visits. However the contribution of wildfire to ED visits for certain diagnoses such as asthma are likely to be substantially higher. Moreover, the totals for all-cause ED visits would be higher absent the behaviorally induced declines under the most extreme conditions. Our attributed increase in ED visits in CA due to wildfire smoke in an average year (3,010) represents about a fifth as many excess ED visits as have been attributed to one of the worst heatwaves in state history (16,166).[5]

While precise quantitative statements about the welfare impact of wildfire smoke are difficult given existing data – e.g. we do not have data with which to price or value the avoidance behavior – qualitative analysis suggests overall welfare losses from smoke but perhaps ambiguous effects on very bad smoke days. Individuals derive many benefits from days with no smoke in the air, including less need to protect themselves with purifiers or masks, increased enjoyment of outdoor spaces, and relative ease in seeking medical care. However, seeking medical care can also create negative externalities, if individuals only pay a portion of the cost of their ED visit and if visits for non-urgent conditions – which can make up a substantial portion of total visits[34,35] – make treatment of urgent conditions more difficult. At low levels of smoke exposure, we find little obvious evidence of avoidance behavior and clear evidence of an increase in ED visits, relative to a day with no smoke; on these days, welfare effects are likely negative. On very smoke days, however, we see a decline in injuries and a reduction in treatment-seeking behavior for a range of non-urgent symptoms; we also see a substantial increase in respiratory-related visits. The net effect of these competing channels depends on the relative size of the harm from the increased respiratory visits and any long-term harm from medical treatment foregone, relative to the benefits of a less-crowded ED and a reduction in so-called 'inappropriate-use' ED visits. While it seems plausible that harms from the former outweigh benefits from the latter, further work is needed to precisely quantify these tradeoffs.

There are a number of potential limitations to our approach. First, our unit of analysis is the zipcode day and thus our exposure metric could be subject to mismeasurement, particularly for zipcodes whose residents typically spend substantial time outside of their home zipcode. The extent and impact of mismeasurement on parameter estimates depends on the spatial covariance of exposure and whether work-related mobility is systematically related to daily wildfire exposure. As earlier work demonstrates strong spatial covariance in exposure (i.e. nearby areas are exposed similarly) and that individuals are more likely to remain in their residence on smoky days,[26] we believe that the impact of this mismeasurement is likely small. Second, our exposure measure reflects ambient conditions and thus does not account for variation in how much ambient pollution filters indoors. Observed differential effects across zipcodes could be partially explained by systematic variations in the extent to which ambient wildfire smoke enters homes,[26] which could itself be further correlated with ED visit rates, though the direction and magnitude of these differences is difficult to predict and a critical area for future work. Third, our wildfire smoke measure is modeled and we do not have uncertainty measures to propagate through our statistical analysis, and thus confidence intervals in our outcomes models might be too small; this is a common challenge in the rapidly growing set of studies that use modeled pollution exposure data to estimate dose-response functions. Fourth, our exposure metric characterizes $PM_{2.5}$ from wildfire smoke, not total $PM_{2.5}$, and marginal effect of smoke $PM_{2.5}$ may differ across levels of non-smoke $PM_{2.5}$. Fifth, while we observe detailed individual level ED visit data, we do not observe direct measurements of injury severity which could allow us to better assess which behavioral mechanisms drive the observed reduction in visits at high smoke intensities. Sixth, we also do not observe visits to urgent care centers or drop-in clinics and thus cannot assess the extent of substitution from ED utilization to other types of healthcare providers.

Wildfire smoke pollution is an increasingly important environmental hazard throughout much of the US and globally. Our work contributes to an increasingly large body of evidence on the negative impacts of wildfire smoke on health. As our ED data end in 2017, we are unable to measure the impacts of the more widespread extreme smoke exposures that occurred in 2018, 2020, and 2021. Further tracking the impact of these exposures will be critical to understanding and adapting to a warming climate, which is expected to make such exposures increasingly common throughout much of the US in coming years.

Figure 1: **Data Summary.** **a** Annual total ED visits in California 2006-2017 broken down by primary diagnosis (see Supplement for ICD codes corresponding to each group). **b** Sub-group breakdown for relevant diagnoses. Black labels indicate broader categories while white labels indicate sub-categories. **c** Annual wildfire smoke frequency in California showing the population-weighted average number of days across the state with wildfire smoke separately by smoke intensity. **d** Histogram of smoke $PM_{2.5}$ concentration on days with smoke present. Nearly half of smoky days 2006-2017 had smoke $PM_{2.5}$ less than 5 $\mu g m^{-3}$ while 5% of smoky days had smoke $PM_{2.5}$ over 50 $\mu g m^{-3}$.

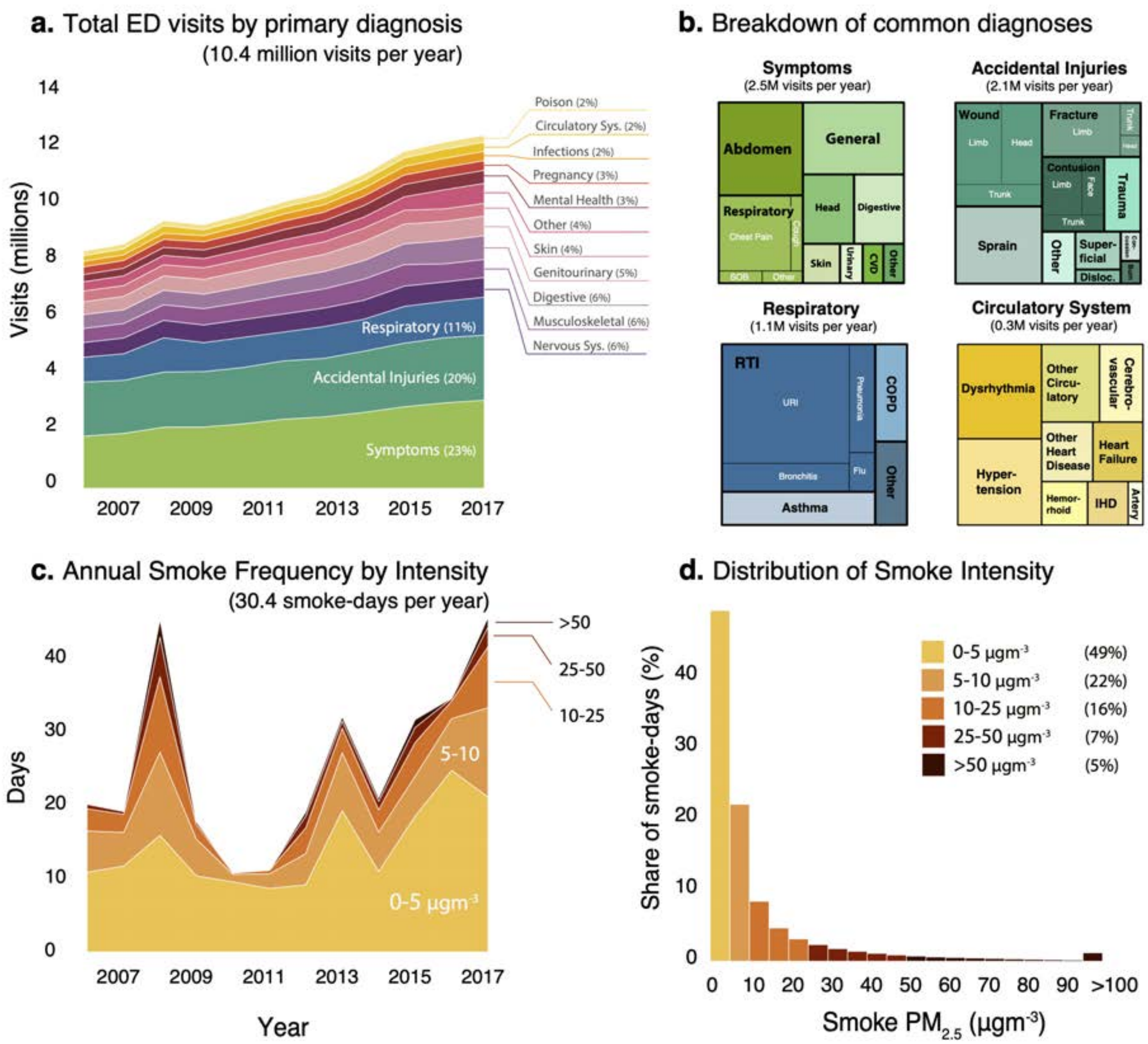


Figure 2: **All-cause ED visits increase with additional exposure to moderate levels of smoke pollution but decline dramatically on the most extreme days**. **a** The estimated all-cause response is derived from a zipcode level distributed lag regression model of daily ED visit rates on a 4th degree polynomial of wildfire smoke intensity measures for the 7 days prior through day-of visit (Equation 2). Coefficient estimates at each level of smoke intensity were summed across lags to estimate the total effect of an additional day at a given exposure intensity on ED visits in the following week. Shaded area indicates bootstrapped 95% confidence interval. Histogram at the bottom shows the distribution of smoke intensity across smoke-days. **b** Responses separated out by primary ICD grouping associated with the principal visit diagnosis. Each response comes from a different regression with that group of ED visits as the outcome in Equation (2). The all-cause response estimated from a separate regression and shown in panel a is plotted in black and reflects the net effect of positive and negative impacts associated with different diagnoses.

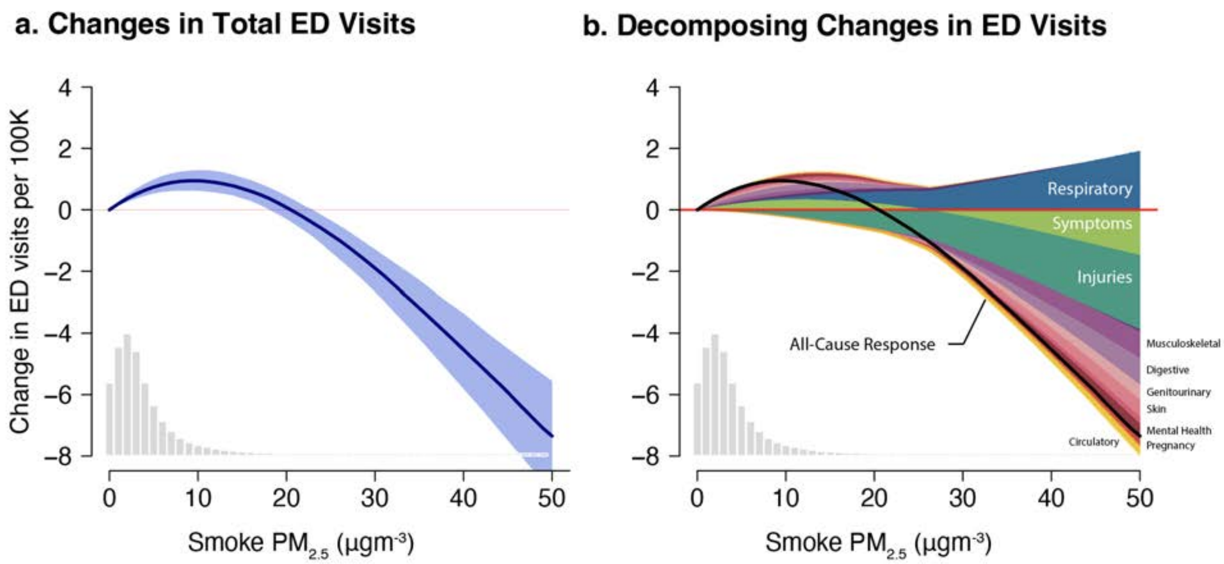


Figure 3: **Responses to wildfire smoke vary by smoke intensity, whether diagnosis is directly exacerbated by pollution, and behavioral mechanism.** Responses shown in terms of percentage change relative to base rate for select diagnoses with primary ICD groupings in the left panel and select sub-category groupings in the right column. Responses are shown for all primary groupings in Fig S6 and for additional sub-groupings in Fig S7, S9-S10. The response in each panel comes from a different binned regression where ED visits with a given principal diagnosis are the outcome. Acronyms in labels: COPD = Chronic obstructive pulmonary disease, IHD = ischemic heart disease.

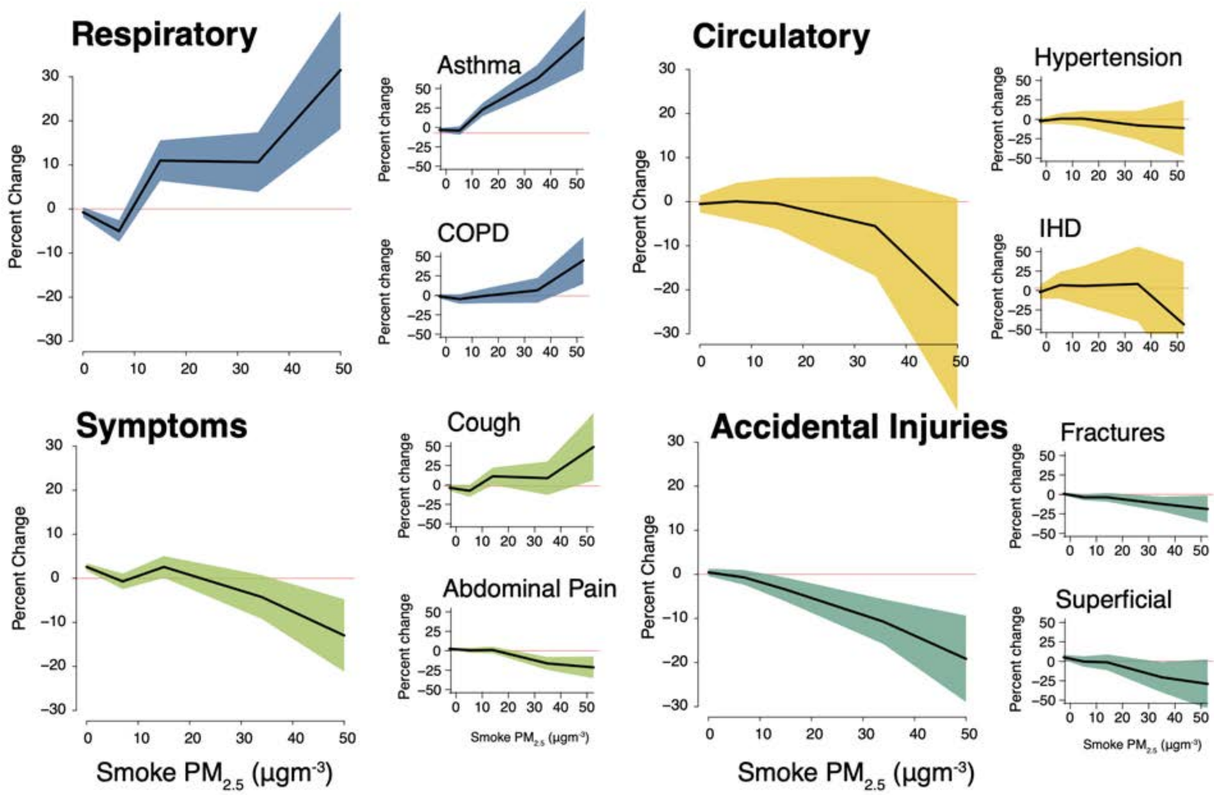
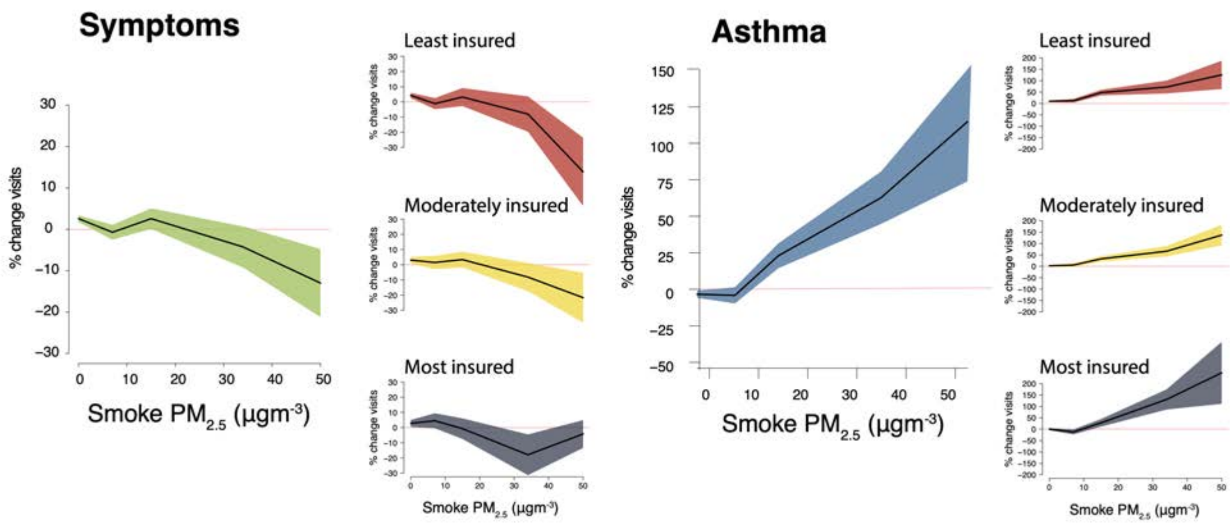


Figure 4: **Declines in ED visits for general symptoms at high smoke $PM_{2.5}$ come primarily from reductions in visits by less insured populations whereas increases in ED visits for respiratory conditions occur regardless of insurance coverage.** Large panels show population-wide responses and small panels show responses estimated in separate regressions subsetting to zipcodes in the bottom, middle, or top tercile of insurance coverage rates. Responses are plotted as percentage changes from group-specific base-rates.



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Supplemental information

Figures

Figure S1: **Trend in ED visit rates over time**. Population-weighted average daily ED visit rates across months of our sample.

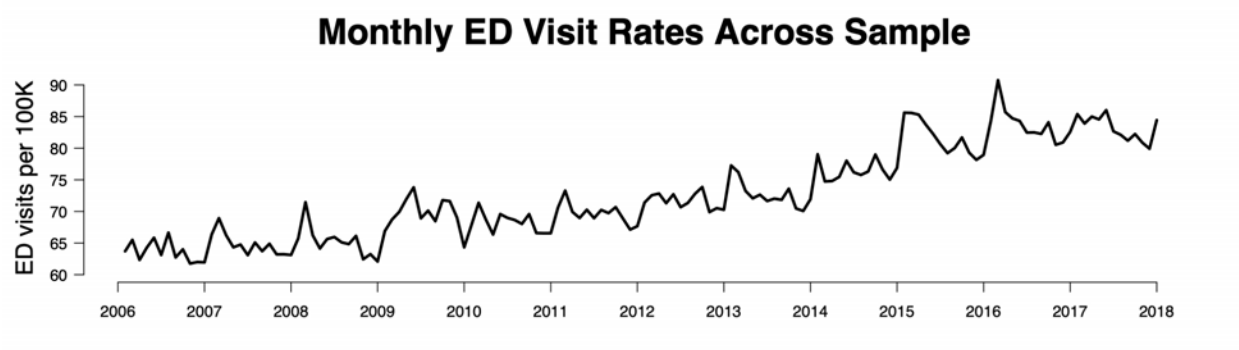


Figure S2: **Spatial patterns of ED visits**. Left panel shows spatial distribution of average zip-code level rates for all-cause ED visits. Right panels show average rates by primary diagnosis. Areas not covered by zip codes are filled in with county-level averages. All maps are colored according to visit rate quantiles in order to highlight the spatial distribution.

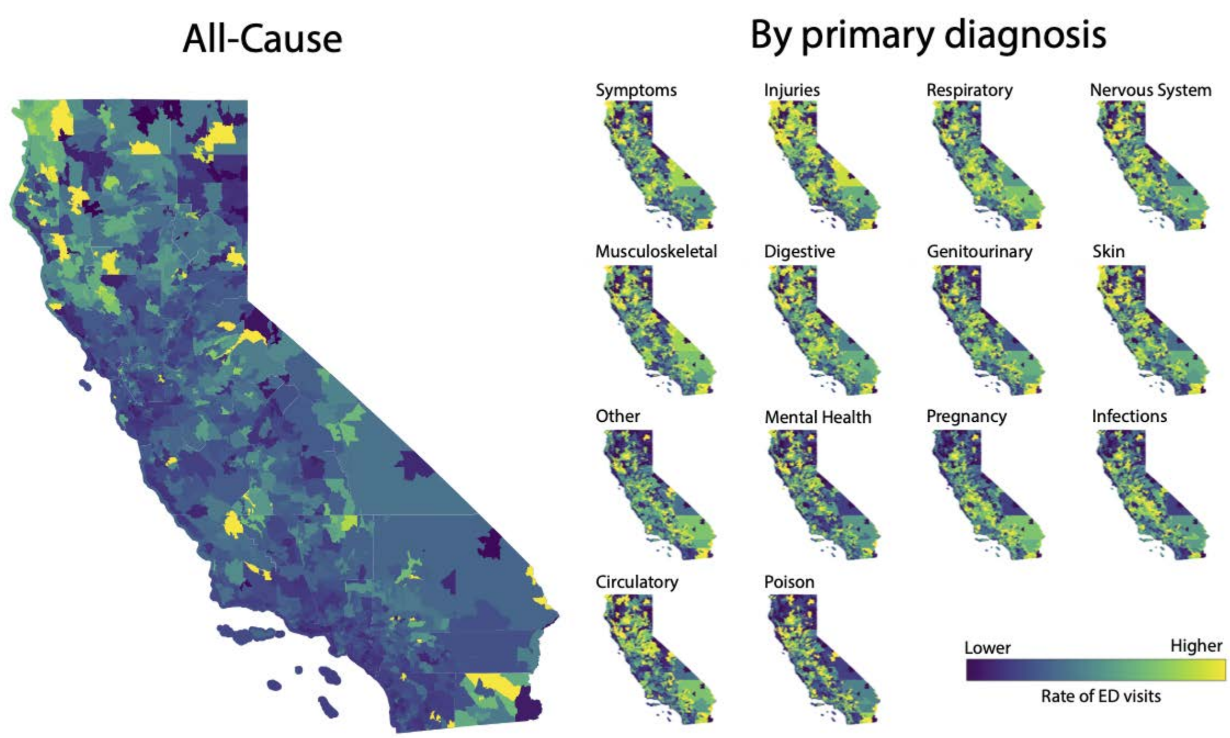


Figure S3: **Seasonality in ED visits by primary diagnosis.** Each panel shows the population weighted month-of-year average daily ED visit rate for a principal diagnosis grouping. Panels are sorted from most (symptoms) to least (poison) frequent diagnosis. To highlight the seasonality in diagnoses with widely varying rates, the vertical axes vary across panels. To quantify the importance of seasonality the maximum-minimum ratio (mmr) is calculated for each diagnosis group as the ratio of the rate in the highest month to the rate in the lowest month and shown in the panel text. Seasonality is largest in ED visits for respiratory conditions with the maximum-minimum ratio (2.5) nearly twice as large as for the next most seasonal condition (poisonings = 1.4). All remaining diagnosis groupings exhibiting smaller month-to-month variation.

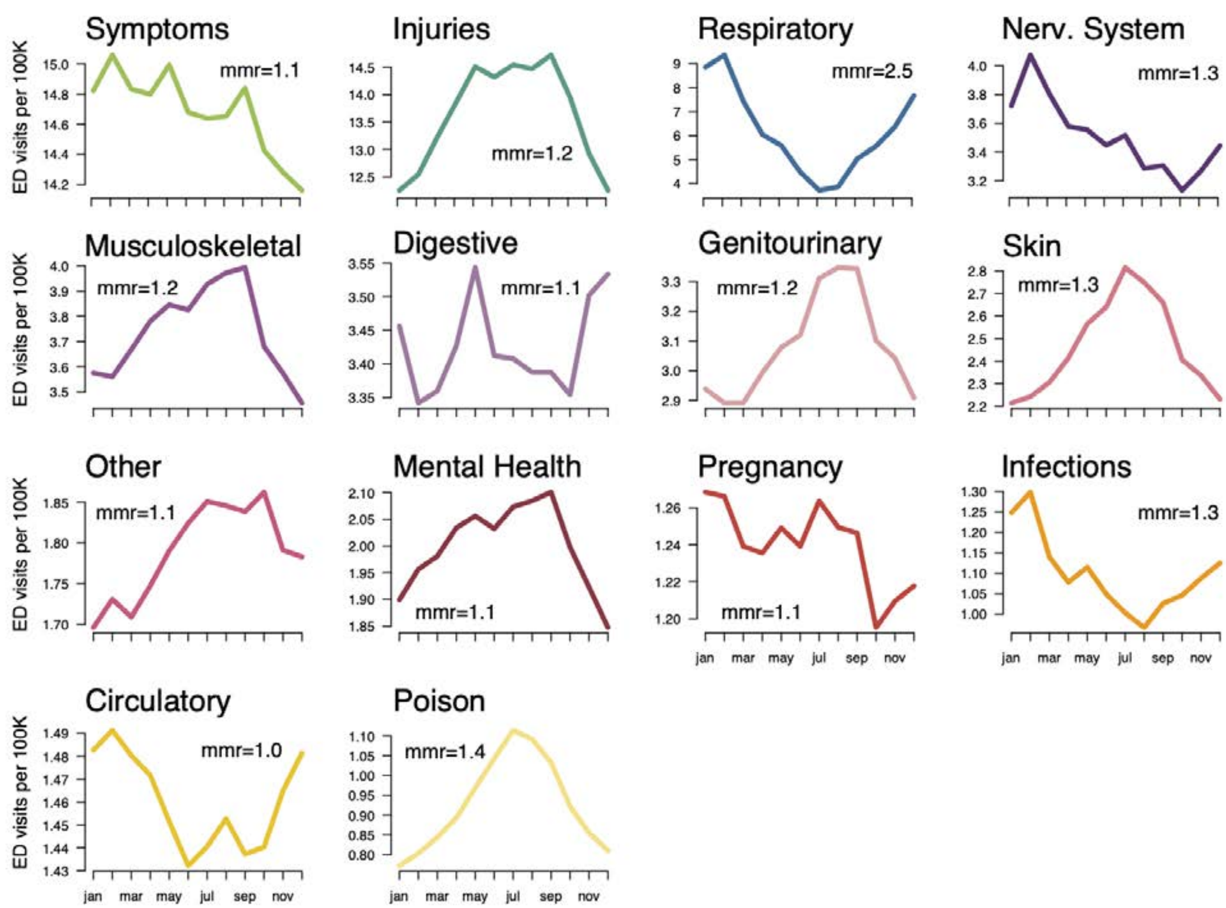


Figure S4: **Estimated response is robust to model functional form choice.** The estimated response of total ED visits to wildfire smoke is shown across different smoke intensity functional forms, choice of fixed effects, lag structures, and with inclusion of different controls. The choices for each dimension used in the main specification are shown in the panel subtitles. (Top left) Results are similar across binned and polynomial specifications. (Top right) Results shown across different choices of fixed effects (cty = county, dow = day-of-week, moy = month-of-year, mos = month-of-sample). (Middle left) Response shape is robust to inclusion of additional lags out to as far as 4 weeks. (Middle right) Response shape is robust to inclusion of non-smoke $PM_{2.5}$, distance traveled to ED, subsetting the sample to different distances away from active fires, and to dropping all covariates beyond wildfire smoke $PM_{2.5}$. (Bottom Left) Poisson model of ED visit counts estimated separately for both 4th degree polynomial and binned specifications of smoke $PM_{2.5}$.

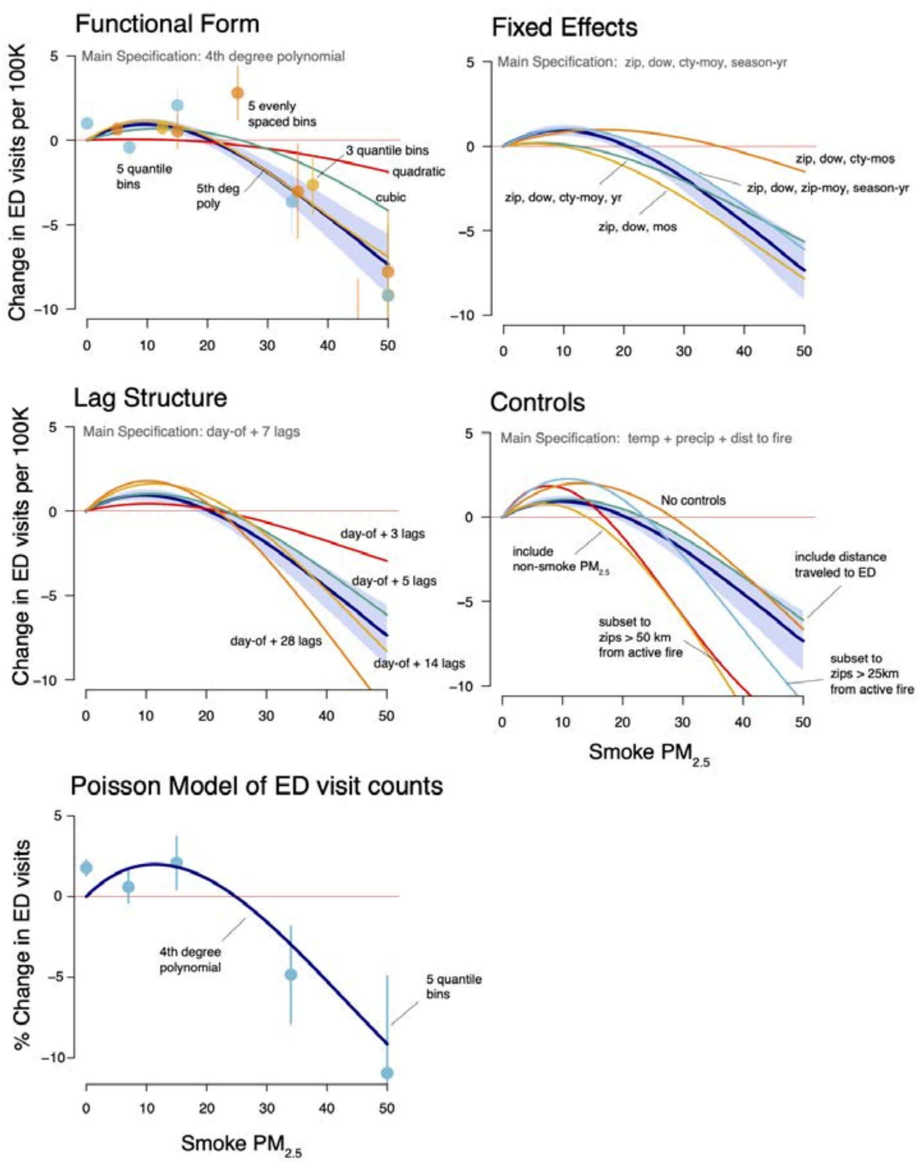


Figure S5: **Proportion of ED visits in California by primary diagnosis.** Figure shows the breakdown of primary diagnoses by group and sub-group (analogous to Figure 1b) for all visits in California 2006-2017. Black labels indicate first-level categories and white labels indicate sub-categories.

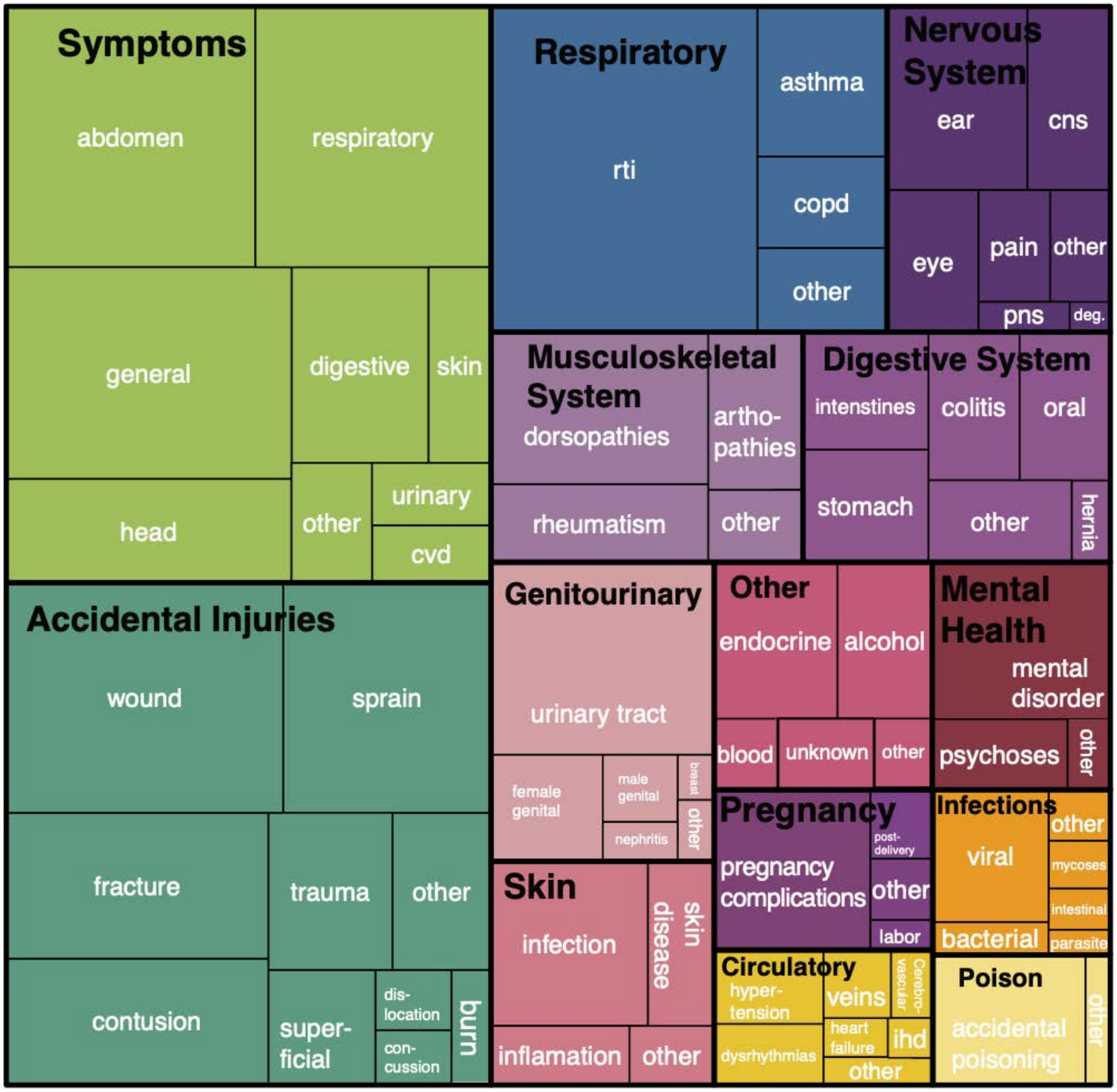


Figure S6: **Average cumulative effects of wildfire smoke on ED visit rates by principal diagnosis ICD grouping 2006-2017 for the 14 primary ICD groupings.** Each response comes from a different regression estimated where the number of visits with a given principal diagnosis is the outcome. All models are specified as binned models with the same controls used in our main specification. To account for multiple hypothesis testing we apply the Bonferroni correction. Confidence intervals therefore reflect $\alpha = 0.05/14$. Base rates shown are daily population weighted average ED visits per 100,000 people with that outcome as the primary diagnosis.

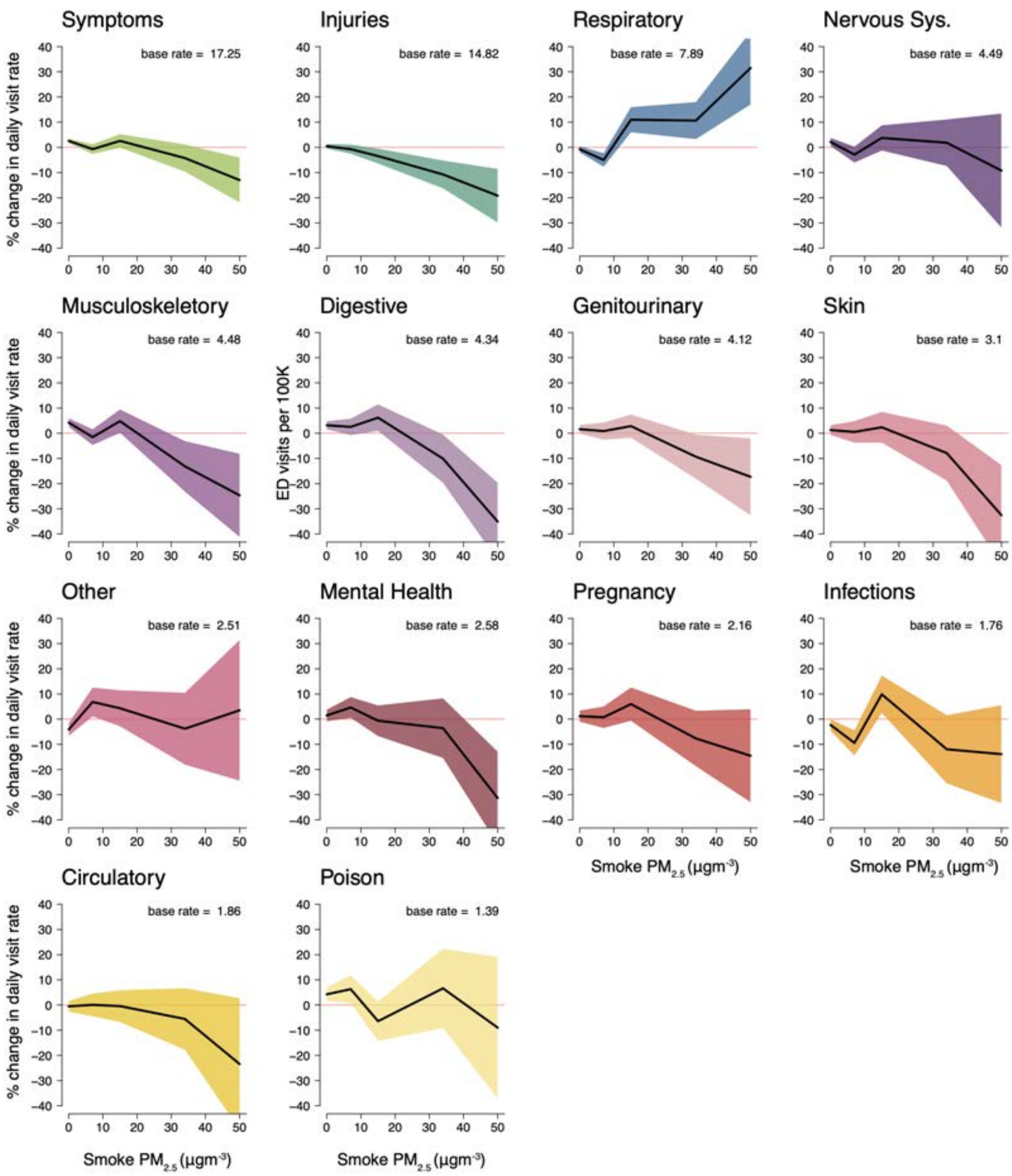


Figure S7: **Cumulative effects of wildfire smoke on ED visits for different types of respiratory conditions.** The response in each panel comes from a different binned regression where ED visits with a given principal diagnosis are the outcome. Shaded areas indicate Bonferroni-corrected 95% confidence intervals. ICD groupings correspond to Figs 1b and S5 and all ICD codes corresponding to each grouping are listed in the supplement. Base rates shown are daily population weighted average ED visits per 100,000 people with that outcome as the primary diagnosis. Acronyms in labels: RTI = respiratory tract infection. URI = upper respiratory infection. Note, as illustrated in Fig 1b, that URI, bronchitis, pneumonia, and influenza are sub-types of RTIs.

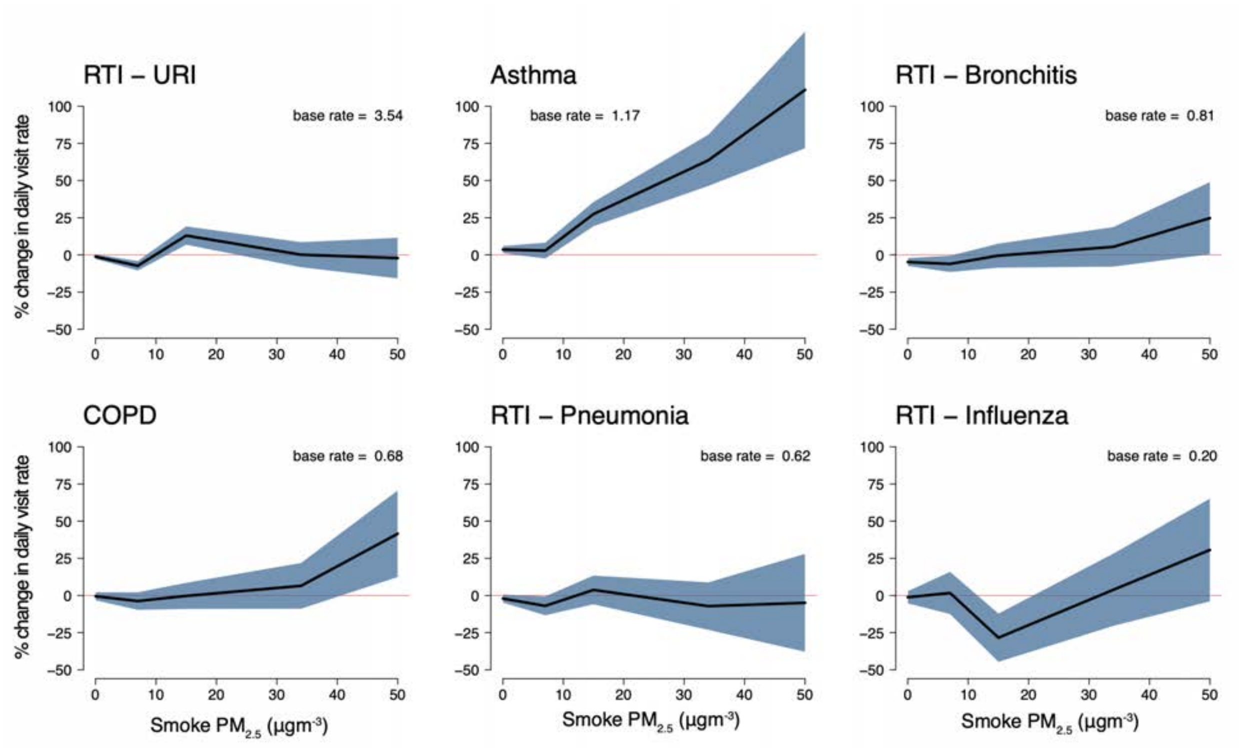


Figure S8: **Contributions of different diagnoses to estimated changes in ED visits in response to wildfire smoke.** Each panel highlights which diagnoses the estimated increases and decreases in ED visits in response to wildfire smoke come from that are shown in Fig 2b. Top panel shows when smoke $PM_{2.5}$ is 10 $\mu g/m^{-3}$ ED visits for most diagnoses increase, with 28% of the increase coming for visits for undiagnosed symptoms. Only accidental injuries and infections show declines in ED visits with most of the decline coming from injuries. At high smoke $PM_{2.5}$=50$\mu g/m^{-3}$ (bottom panel) only ED visits for respiratory conditions increase. Visits for all other diagnoses decline.

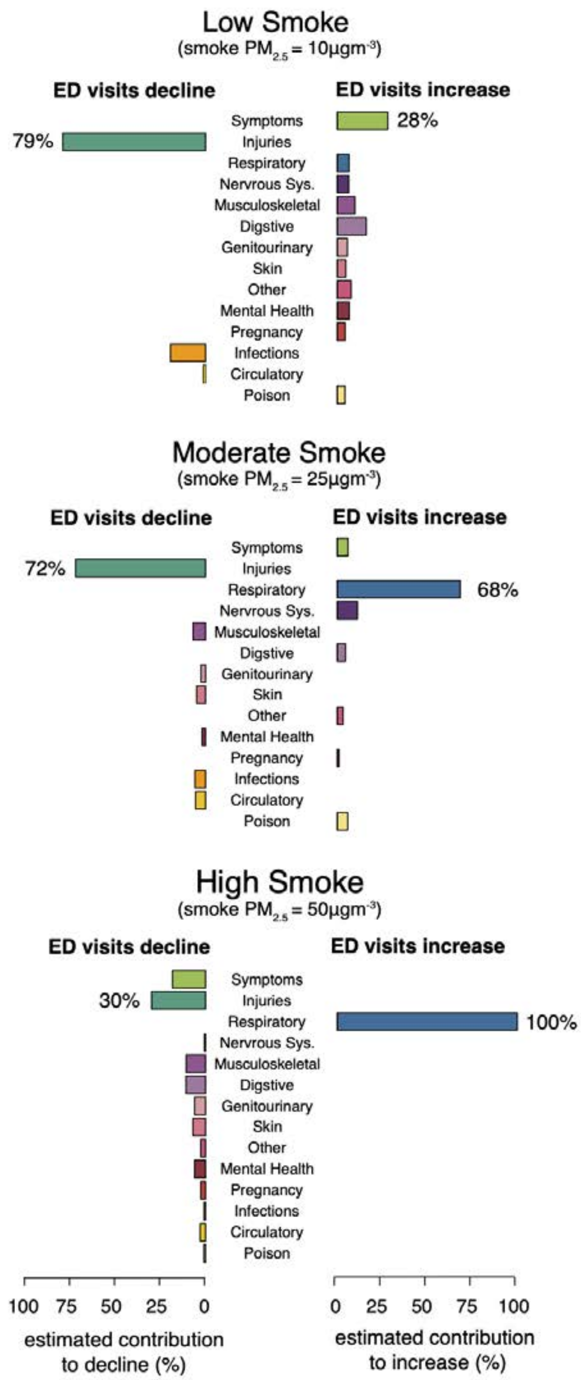


Figure S9: **Cumulative effects of wildfire smoke on ED visits for different symptoms.** The response in each panel comes from a different binned regression where ED visits with a given principal diagnosis are the outcome. Shaded areas indicate Bonferroni-corrected 95% confidence intervals. ICD groupings correspond to Figs 1b and S5 and all ICD codes corresponding to each grouping are listed in the supplement. Base rates shown are daily population weighted average ED visits per 100,000 people with that outcome as the primary diagnosis. Acronyms in labels: CVD = cardiovascular system.

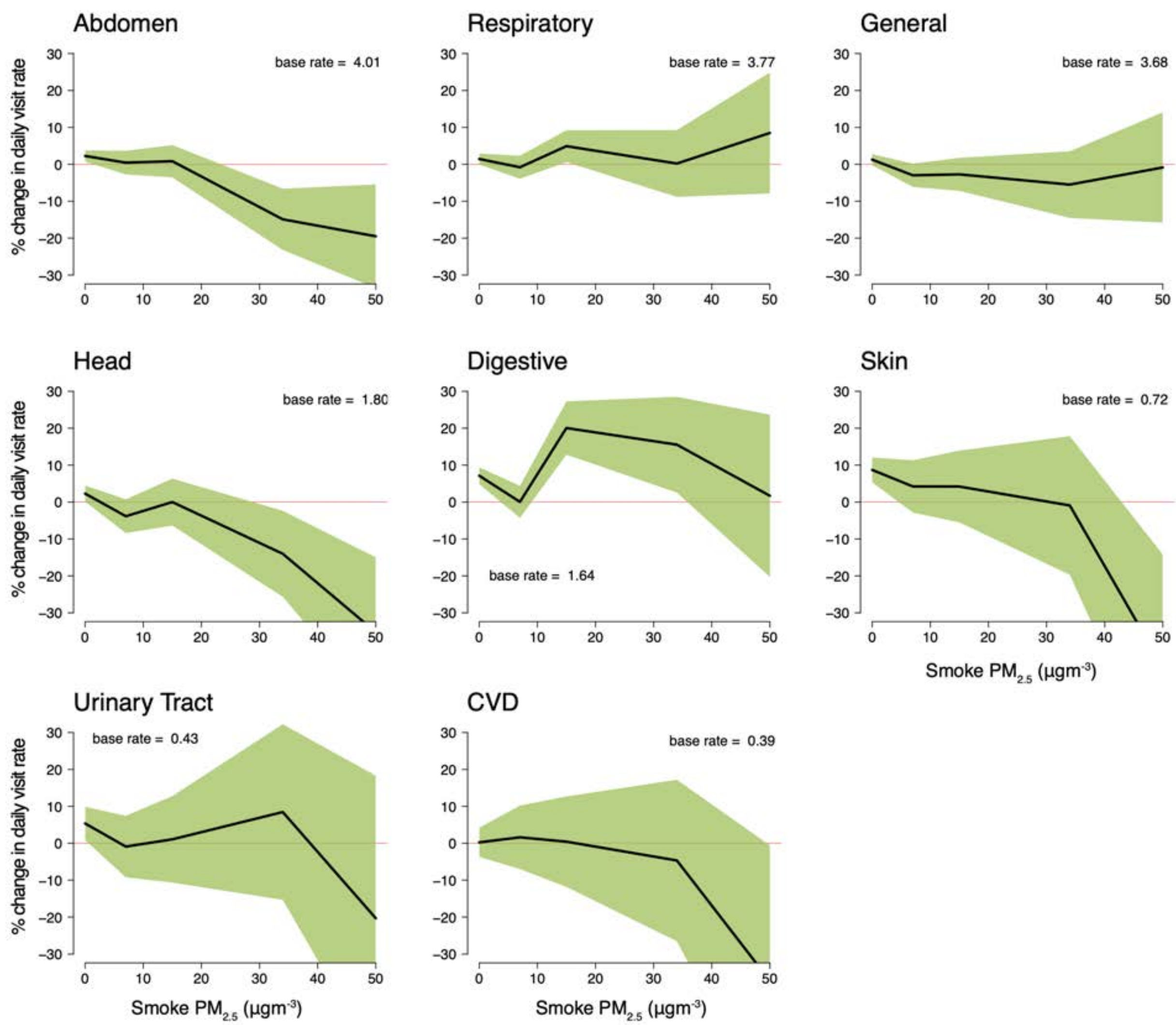


Figure S10: **Cumulative effects of wildfire smoke on ED visits for different types of accidental injuries.** The response in each panel comes from a different binned regression where ED visits with a given principal diagnosis are the outcome. Shaded areas indicate Bonferroni-corrected 95% confidence intervals. ICD groupings correspond to Figs 1b and S5 and all ICD codes corresponding to each grouping are listed in the supplement. Base rates shown are daily population weighted average ED visits per 100,000 people with that outcome as the primary diagnosis.

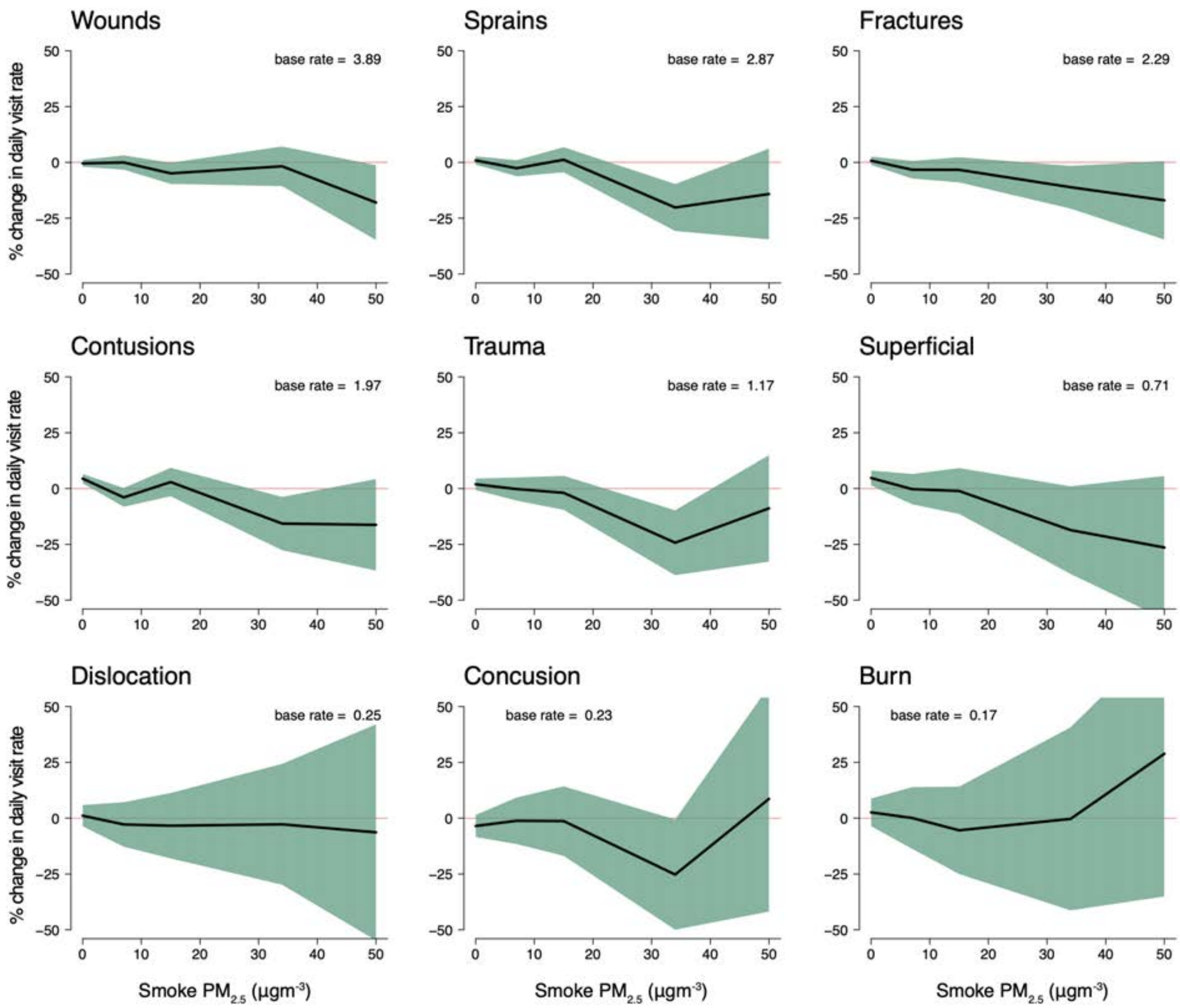


Figure S11: **All-cause ED visit response to wildfire smoke by age group.** The cumulative effects of wildfire smoke on all-cause ED visits for different age groups. Results come from five different regressions, one for each age group, with age specific zip by day ED visit rates as the outcome. Regressions are weighted by the group-specific zip code population. Responses show the cumulative impact of wildfire smoke $PM_{2.5}$ across the day of ED visit and each day in the preceding week. The increase in total visits at moderate smoke $PM_{2.5}$ levels is driven by additional visits by children under 5 while the declines observed at high smoke $PM_{2.5}$ concentrations are driven by changes in the number of visits by adults.

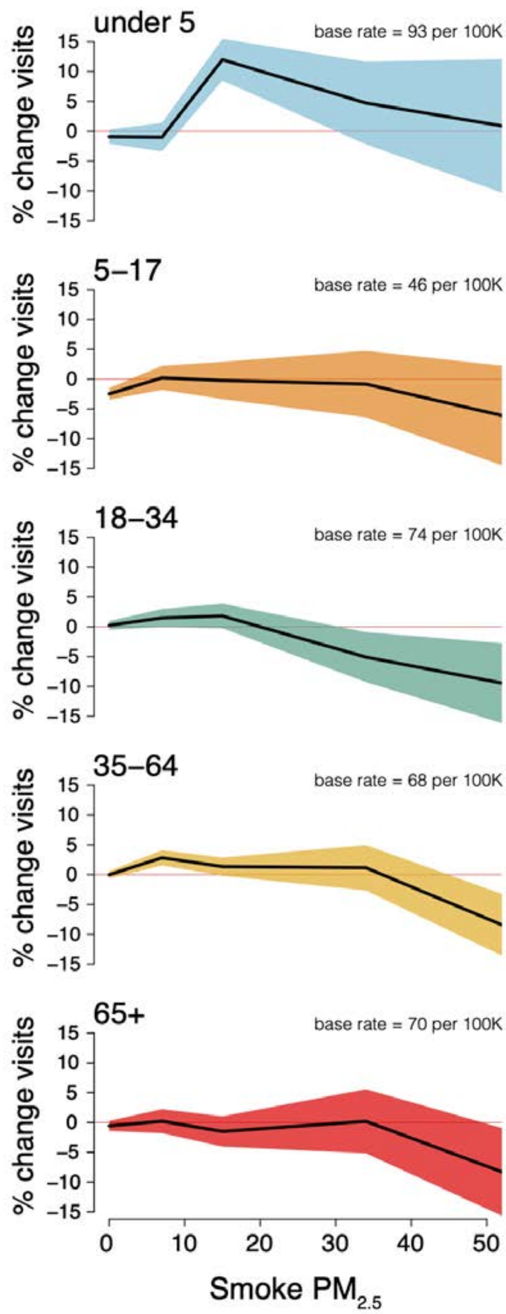


Figure S12: **Insurance coverage is correlated with other measures of vulnerability.** The sample split by share of population insured used is Fig 4 is shown here but for the distribution of different factors. (a) shows the sample split with insurance coverage rates, the measure used to generate the split shown in Fig 4. The population that is least insured is more likely to receive insurance from a public provider (b), has higher rates of ED visits (c), has lower income (e) and higher rates of non-English speakers (f). The distance from home zip code to the nearest is ED is similar across groups (d). Colored lines on the x-axis indicate median values for corresponding group.

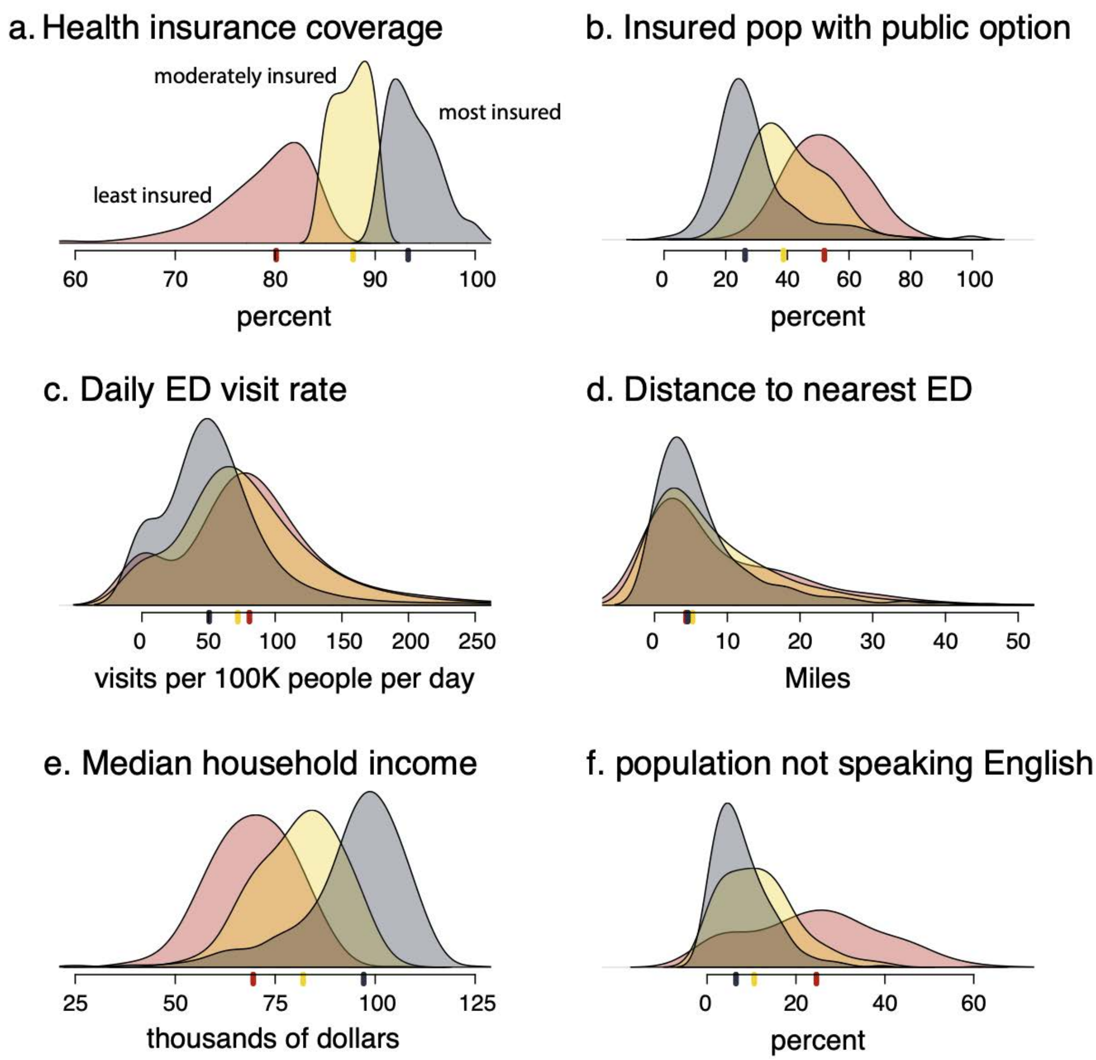
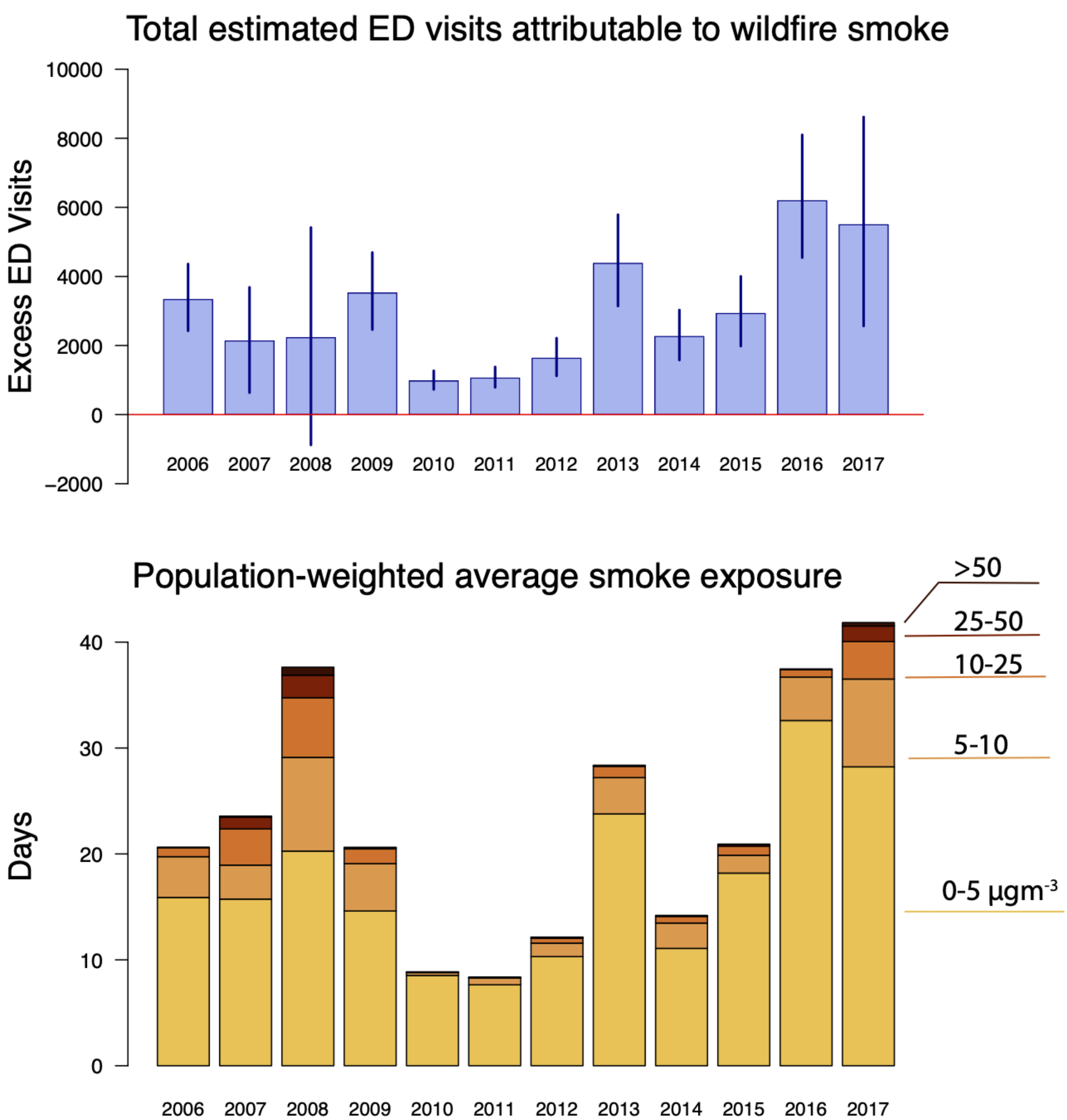


Figure S13: **Annual all-cause ED visits attributable to wildfire smoke.** We apply the estimated response curve shown in Fig 2 to estimated smoke $PM_{2.5}$ concentrations[24] in order to estimate the annual number of excess ED visits attributable to smoke during our sample period (top). The height of the bar indicates the main estimate and the vertical lines show the 95% CI. While our estimated response curve indicates sharp declines in total ED visits at high smoke intensities, most smoke-days are low to medium intensity which leads to an overall increase in ED visits attributable to smoke. The bottom panel shows population-weighted average exposure by smoke intensity. While 2008 and 2016 had a similar number of total days with smoke exposure, there were far more high intensity smoke days in 2008 (bottom) leading to that year having less than half the estimated attributable ED visits as 2016 (top).



ICD Groupings Excel file with comprehensive list of outcomes and corresponding ICD-9 and ICD-10 codes can be downloaded here.