# Epidemiology

## Wildfire exposure and health care use among people who use durable medical equipment in Southern California

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**Abstract:**

Background

People using electricity-dependent durable medical equipment (DME) may be particularly vulnerable to health effects from wildfire smoke, residence near wildfires, or residence in evacuation zones. No studies have examined their healthcare utilization during wildfires.

Methods

We obtained 2016-2020 daily counts of residential Zip Code Tabulation Area (ZCTA) level outpatient, inpatient, and emergency department visits made by DME-using Kaiser Permanente Southern California members 45+. We linked counts to daily ZCTA-level wildfire $PM_{2.5}$ estimates and wildfire boundary and evacuation data from the 2018 Woolsey and 2019 Getty wildfires. We tested the association of immediate and lagged (up to 7 days) wildfire $PM_{2.5}$ and wildfire proximity and evacuation and healthcare visit frequency with negative binomial and difference-in-differences models.

Results

Among 236,732 DME users, increased wildfire $PM_{2.5}$ concentration (per 10 [[EQUATION]] ) was associated with reduced risk (RR = 0.96, 95% CI: 0.94, 0.99) of all-cause outpatient visits one day after exposure and increases on 4/5 subsequent days (RR range 1.03-1.12). Wildfire $PM_{2.5}$ was not associated with inpatient or ED visits. Woolsey Fire proximity (<20km) was associated with reduced all-cause outpatient visits, while evacuation and proximity were associated with increased inpatient cardiorespiratory visits (proximity RR = 1.48, 95% CI: 1.01, 2.17, evacuation RR = 1.76, 95% CI: 1.02, 3.05). Neither Getty Fire proximity nor evacuation was

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| | associated with healthcare visit frequency.<br><br>Conclusions<br><br>Wildfire smoke or proximity may interrupt DME users' outpatient care, as patients at risk may shelter in place. However, smoke and fire still appeared to increase healthcare utilization in this vulnerable group. |
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*Epidemiology*

re: “Wildfire exposure and healthcare use among people who use durable medical equipment in Southern California”

Dear Dr. Lash,

Individuals relying on electricity-dependent medical equipment (DME) are likely particularly vulnerable to both wildfire smoke exposure and health effects from evacuation. Prior studies, many in *Epidemiology*, have examined the association between wildfire $PM_{2.5}$ and emergency department use and hospitalizations, primarily using claims data. However, none have evaluated smoke exposure among DME users or the health implications of residential proximity wildfire, including evacuations.

We quantified the effects of wildfire $PM_{2.5}$ on outpatient, inpatient, and emergency visit rates among Kaiser Permanente DME users in Southern California using electronic health record data. We find outpatient visits decreased by 1-13% for a week after a 10 $\mu g/m^3$ increase in wildfire $PM_{2.5}$. We also identified patients living nearby and in the evacuation zones of two major wildfires, and with a difference-in-differences design find a decrease in outpatient visits, and an increase in inpatient admissions, during the larger of the two fires.

Other studies have documented increases in emergency and inpatient healthcare use but wildfire smoke and evacuations may interrupt outpatient care in this vulnerable population.

The manuscript and data have not been previously published, either in whole or in part, and no similar paper is in press or under review elsewhere. We have no conflicts of interest or closely related papers.

Sincerely,

Heather McBrien, Sebastian Rowland, Tarik Benmarhnia, Sara Tartof, and Joan Casey

# Original research article: Wildfire exposure and health care use among people who use durable medical equipment in Southern California

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Abbreviated title: DME users may be vulnerable to wildfire smoke and evacuation

No authors have a conflict of interest.

All of our code is publicly available for download at github.comheathermcb/wildfires_and_DME, but our data is privately shared from Kaiser Permanente Southern California, and therefore cannot be made public.

This paper is supported by the National Institute on Aging RF1AG071024.

We acknowledge Dr. Robbie Parks for his publicly downloadable temperature processing scripts used in our data pipeline.

# Abstract

**Background:** People using electricity-dependent durable medical equipment (DME) may be particularly vulnerable to health effects from wildfire smoke, residence near wildfires, or residence in evacuation zones. No studies have examined their healthcare utilization during wildfires.

**Methods:** We obtained 2016-2020 daily counts of residential Zip Code Tabulation Area (ZCTA) level outpatient, inpatient, and emergency department visits made by DME-using Kaiser Permanente Southern California members 45+. We linked counts to daily ZCTA-level wildfire $PM_{2.5}$ estimates and wildfire boundary and evacuation data from the 2018 Woolsey and 2019 Getty wildfires. We tested the association of immediate and lagged (up to 7 days) wildfire $PM_{2.5}$ and wildfire proximity and evacuation and healthcare visit frequency with negative binomial and difference-in-differences models.

**Results:** Among 236,732 DME users, increased wildfire $PM_{2.5}$ concentration (per 10 $\mu g/m^3$) was associated with reduced risk (RR = 0.96, 95% CI: 0.94, 0.99) of all-cause outpatient visits one day after exposure and increases on 4/5 subsequent days (RR range 1.03-1.12). Wildfire $PM_{2.5}$ was not associated with inpatient or ED visits. Woolsey Fire proximity (<20km) was associated with reduced all-cause outpatient visits, while evacuation and proximity were associated with increased inpatient cardiorespiratory visits (proximity RR = 1.48, 95% CI: 1.01, 2.17, evacuation RR = 1.76, 95% CI: 1.02, 3.05). Neither Getty Fire proximity nor evacuation was associated with healthcare visit frequency.

**Conclusions:** Wildfire smoke or proximity may interrupt DME users' outpatient care, as patients at risk may shelter in place. However, smoke and fire still appeared to increase healthcare utilization in this vulnerable group.


**Keywords:** Durable Medical Equipment, wildfire, wildfire smoke, wildfire evacuation, healthcare utilization, disaster evacuation, climate change

# Introduction

Wildfires are widespread, have increased in severity because of climate change, and will worsen in coming decades.[1–5] Development in the wildland-urban interface has placed more communities in the path of these increasingly frequent disasters.[6] The immediate impacts of wildfire, such as evacuations, power outages, and destruction of infrastructure cause trauma, stress, financial strain, and physical injury in affected communities.[7,8] Simultaneously, 70% of the US population is exposed to wildfire smoke annually as winds blow smoke over major cities.[9–11]

Among other hazardous components, wildfire smoke contains fine particulate matter ($PM_{2.5}$). Of $PM_{2.5}$ sources, wildfire $PM_{2.5}$ may be particularly harmful because it consists of more organic and elemental carbon.[12–14] It also constitutes most extreme $PM_{2.5}$ exposure in California, accounting for 71% of total $PM_{2.5}$ on days that exceed US Environmental Protection Agency (USEPA) annual standard of 12 $\mu g/m^3$.[9]

Most studies examining wildfire PM2.5 exposure have focused on respiratory and cardiovascular disease outcomes. Exposure has been associated with asthma and chronic obstructive pulmonary disease symptom exacerbation,[15–17] increases in ED and inpatient visits related to cardiorespiratory disease,[18–21] and increased mortality risk.[22–24]

Despite this robust understanding of wildfire smoke exposure, few studies[21,25–27] have examined smoke exposure in vulnerable populations, or wildfire-related exposures other than smoke. Only descriptive research has documented the effects of stress, evacuation, property destruction, or injury due to wildfire disasters.[7,8,28] We hypothesize that residential proximity to wildfire, and evacuations due to wildfire, could influence health outcomes primarily through stress. Residents living near active wildfires are exposed to smoke, experience the disruption of usual activities in their communities, and face the threat of injury, evacuation, or longer-term displacement. Evacuation may cause more severe stress as these threats materialize.

People who use durable medical equipment may be particularly vulnerable to both wildfire $PM_{2.5}$ exposure and stress from wildfire proximity or evacuation. DME use is common among older adults and is associated with respiratory illness and other disabilities.[29] A prior study among Kaiser Permanente Southern California (KPSC) members found increasing prevalence of DME rentals from 2008-2018 and the highest prevalence of use among older adults.[30] DME types included bilevel positive airway pressure (BiPAP) machines, enteral feeding machines, infusion pumps, oxygen equipment, suction pumps, ventilators, and wheelchairs.[30]

This group may face unique challenges during wildfire events. Prior studies have found elevated effect estimates between wildfire smoke exposure and respiratory and cardiovascular disease outcomes among older adults compared to younger populations.[16,31] Further, people using DME may have co-occurring medical conditions such as cardiovascular disease that make them more vulnerable to both the effects of wildfire $PM_{2.5}$ and wildfire-related stressors beyond wildfire smoke (e.g., threatened or actual evacuation). Limited mobility or need for electricity access may result in increased difficulty evacuating disaster zones.[30,32]

Here, we use 2016-2020 Kaiser Permanente Southern California (KPSC) electronic health records of older adults using DME from seven Southern California counties to examine the relationship between wildfire exposure and healthcare utilization. We evaluate exposure to wildfire via (1) wildfire $PM_{2.5}$ concentrations, and by (2a) residential proximity to major active fires, and (2b) residence in an evacuated area. Our study period includes two major wildfire events in populated areas: the Woolsey Fire, which burned around 400km$^2$ from November 8th to 21st, 2018 in Los Angeles and Ventura counties, destroying 1643 structures, displacing 295,000 people, and killing three,[33,34] and the Getty Fire, which necessitated evacuations in densely populated Los Angeles, and burned 3km$^2$ from October 28th to November 5th, 2019.[35,36]

# Methods

## Study population and outcome data

We used electronic health record data from KPSC to identify all individuals who were 45 or older as of October 28th, 2019 and had rented DME in the year prior. We obtained daily counts of healthcare visits by this population at the Zip Code Tabulation Area (ZCTA) level, in seven counties in Southern California from January 1st, 2016 to March 15th, 2020. 236,732 DME patients lived in the study area, which covered most of San Bernardino, Orange, Los Angeles, Riverside, San Diego, Ventura, and Kern counties (Figure 1). The area consisted of 582 ZCTAs, each containing 1-1773 patients. During 2018 and 2019, these seven counties experienced 23 wildfires that each burned over 3 km$^2$ in California,[34,36] contributing to wildfire smoke in the area.

The KPSC Institutional Review Board (IRB) approved this study, and the Columbia IRB did not consider it human subjects research.

## Exposure Definition

### Wildfire $PM_{2.5}$

We measured wildfire smoke exposure by estimating daily wildfire and non-wildfire $PM_{2.5}$ concentrations at the ZCTA level using a multistage approach described elsewhere.[37] Briefly, we first estimated daily levels of $PM_{2.5}$ (from any source) at the ZCTA level using a validated ensemble model combining multiple machine learning algorithms (e.g., random forest, gradient boosting) and multiple predictors (e.g. meteorological factors such as temperature, precipitation or wind patterns, satellite-derived aerosol optical depth or land-use variables). We identified smoke-plume exposed ZCTA codes/days with the National Oceanic and Atmospheric Administration's (NOAA) Hazard Mapping System (HMS) using a smoke binary variable by intersecting ZCTA polygons with smoke polygons. We then estimated the counterfactual $PM_{2.5}$ values in the absence of wildfire smoke using spatio-temporal imputation models. We finally estimated the difference between such counterfactual values to observed values during an exposure to wildfire smoke to estimate daily/ZCTA levels of wildfire smoke $PM_{2.5}$. We also obtained daily/ZCTA levels of non-wildfire $PM_{2.5}$.

We calculated daily wildfire and non-wildfire $PM_{2.5}$ by averaging concentrations across the higher-level ZCTA groupings (hereafter ZCTA groupings) described in the outcome definition section.

**Proximity to wildfire**

To measure direct exposure to wildfire, we obtained data on the fire boundaries and evacuation zones of two significant Southern California wildfires – the Woolsey Fire and the Getty Fire. We chose these fires because they affected a significant number of people in our study area, during the study period. The Woolsey Fire, which burned from November 8th, 2018 until November 21st, 2018, required the evacuation of 295,000 people from Los Angeles and Ventura counties. It burned 1643 structures and almost 400 $km^2$ of land, making it particularly destructive.[33,36] The Getty Fire, which ignited on October 28th, 2019 and burned until November 5th, 2019, was notable because it necessitated evacuations during its 9-day duration in densely populated Los Angeles.[34,35]

Notably, The Thomas Fire also burned over 1100 $km^2$ during our study period.[38] However, most of the fire burned in the rural northern corner of Ventura County and outside the study area. Therefore, we did not include the Thomas Fire in the proximity analyses. Still, smoke from this fire contributed significantly to wildfire $PM_{2.5}$ in Ventura County in December 2017 (Figure 2b).

We obtained shapefiles of the total areas burned during the Getty and Woolsey fires from the CALFIRE Fire and Resource Assessment Program.[39] Fire boundaries expanded while the fires were active, but fire perimeters recorded during the fires did not differ significantly from the total burned areas of either fire, since dynamic boundary data available did not include perimeters from very early in either fire.[40] We therefore used final fire perimeters to define exposure. We considered ZCTAs exposed if they were within 20km of a final fire perimeter on days that a fire was active. We hypothesized that living within 20km of a fire perimeter could elicit a stress response, similar to effects described in previous studies.[7,8,41]

Next, we created an evacuation exposure metric. GIS data on evacuation zones were not available for either fire. Therefore, we reviewed webpages (described in the eAppendix) containing maps of the evacuation zones and digitized boundaries around all areas ever evacuated during either fire in QGIS[42] (Figure 1). Using these data, we considered ZCTAs exposed to evacuation stress if they were within 10 km of any evacuation zone boundary (Figure 1) on days where a fire was active. Like close residence to a wildfire burn area, evacuation and anticipating potential fire or evacuation can cause stress, which we aimed to capture with this exposure definition.[7,8,41] We chose a 10km buffer rather than the previous 20km buffer because evacuation zones themselves can be large.

## Outcome Definition

We obtained daily counts of all-cause outpatient visits, all-cause inpatient admissions, and all-cause emergency department (ED) visits, as well as inpatient admissions and ED visits specifically for circulatory or respiratory disease outcomes made by KPSC members 45 and older who rented DME. Causes were identified using *International Classification of Diseases* 10 codes I00-I99 and J00-J99, respectively. We included visits from January 1st, 2016 to March 15th, 2020.

Daily visit counts by ZCTA were low and often zero (median outpatient visits = 1, IQR = 3, median ED and inpatient visits = 0, IQR = 0). For the wildfire PM2.5 analyses, to avoid zero-inflation in our models, we could have aggregated ZCTA counts to the weekly level. However, prior studies of wildfire smoke exposure have found associations between same-day air pollution and healthcare visits over the course of the following week.[18–21] To evaluate a lagged effect in our data, we required daily healthcare visit counts, therefore, we opted to aggregate our data into higher-level spatial groupings of several ZCTAs based on spatial proximity (hereafter 'ZCTA groupings'; grouping method described in the eAppendix).

For proximity and evacuation analyses, we used ZCTA level daily visit counts aggregated to the weekly level. Because our exposure data was not as granular as that in the $PM_{2.5}$ analyses, as we used final fire boundaries and final evacuation zones rather than daily data, we evaluated relationships at the weekly level. This aggregation also removed weekend-weekday patterns in outpatient visits and prevented zero inflation. We considered a week exposed if the Woolsey or Getty fire burned any day that week.

## Analysis

### Wildfire $PM_{2.5}$

To evaluate the relationship between daily wildfire $PM_{2.5}$ and daily ZCTA grouping-level healthcare visit counts, we used negative binomial regression. Many studies on lagged effects of air pollution use constrained distributed lag models to estimate stable coefficients in the presence of highly autocorrelated (and therefore highly co-linear) lagged exposures.[43] We examined the autocorrelation of wildfire $PM_{2.5}$ concentrations and found only weak autocorrelation (lags 1-7 days each had <0.25 correlation with lag 0). Unlike other sources of air pollution, wildfire $PM_{2.5}$ concentrations increased dramatically on certain days, then decreased just as quickly (Figure 2b). We therefore created unconstrained models, including separate terms for wildfire $PM_{2.5}$ lags 0-7 days. We also performed an additional analysis examining weekly wildfire $PM_{2.5}$ levels lagged up to two weeks. We created separate models for each healthcare visit type: all-cause outpatient, inpatient, and ED visits, and inpatient and ED visits for circulatory or respiratory disease endpoints.

We included offsets accounting for the number of KPSC members over 45 using DME in each ZCTA grouping. We controlled for temperature using a penalized spline term, as temperature can predict respiratory and cardiovascular healthcare utilization[44] and wildfire,[45] using daily temperature data from the PRISM Climate Group.[46] We also controlled for long-term seasonal trends not caused by exposure with a natural spline term, and used the number of years in the study period (four) to determine the natural spline flexibility (12 degrees of freedom). We controlled for non-wildfire $PM_{2.5}$, since non-wildfire PM 2.5 concentrations were high during the study period: mean daily non-wildfire PM2.5 by grouping was 11.0 $\mu g/m^3$ (SD = 6.69), just under the annual USEPA exposure limit of 12 $\mu g/m^3$ (Figure 2a). We also added a fixed effect for weekends to the outpatient visits model, accounting for fewer visits on weekend days.

We included fixed effects for a comprehensive set of socioeconomic variables to account for correlation between ZCTA groupings. We obtained values by ZCTA from the 5-year 2015-2019 ACS[47] including median household income, home ownership (% homes occupied by owner), poverty (percent households below threshold income), age structure (percent of population 20-64, and 65+ years), and racial/ethnic composition (percent Hispanic, percent non-Hispanic white, percent non-Hispanic Black). We took a simple mean within ZCTA groupings to obtain average covariate values by ZCTA grouping or summed within ZCTA groupings when appropriate (for example, we summed total population across groupings).

**Proximity to wildfire and evacuation**

To evaluate proximity to and evacuation from wildfire, we used a difference-in-differences (DID) analysis with negative binomial regression to estimate the associations between wildfire proximity and evacuation and weekly ZCTA-level healthcare visit counts. We evaluated each relationship separately for each fire and each type of healthcare visit, performing 20 regression analyses. The DID estimators subtracted the change in visit frequency during a fire among control ZCTAs (difference 1) from the change in visit frequency during a fire among ZCTAs exposed to the fire or evacuation zone (difference 2). If all models were specified correctly and parallel trends conditions were met, the DID estimator corresponded to the difference in visit frequency attributable to direct wildfire exposure. We assessed the parallel trends assumption visually (plots are included in the eAppendix).

To avoid bias in our analyses, we chose control ZCTAs by excluding ZCTAs exposed to both the Getty and Woolsey Fires, and excluding all ZCTAs exposed to other large fires (>500 km2 ). However, we felt that ZCTAs exposed to other fires would serve as ideal comparison groups prior to their exposure to those fires. Therefore, we excluded observations from these ZCTAs made during and after fire exposures. We used a CALFIRE fire perimeter data[36] to identify all fires > 500 $km^2$, and excluded data from ZCTAs within 20 km of any of these fire boundaries, from the fire ignition date onward.

As in the wildfire $PM_{2.5}$ models, we included offsets accounting for the population exposed and controlled for temperature with a penalized spline. We controlled for long-term seasonal trends not caused by exposure with a penalized spline term, as our data in these analyses were at the weekly level. We did not control for wildfire $PM_{2.5}$ in these proximity and evacuation models, as we considered this a mediator rather than a confounder.

We tested all models for sensitivity to parameterization of splines, by re-running all analyses with natural splines in place of penalized splines. We conducted all analyses in R,[48] using the mgcv package.[49] All analysis code and model equations are available on GitHub at https://github.com/heathermcb/wildfires_DME.

# Results

## Health data description

The study population consisted of 236,732 KPSC DME users who between January 1, 2016 to March 15th, 2020 had a daily average of 2.5 (SD = 4.7) outpatient visits, 0.1 (SD = 0.4) inpatient visits, and 0.1 (SD = 0.5) ED visits per ZCTA grouping. There were on average 8 (SD = 8.9) outpatient visits per week per ZCTA, 0.2 (SD = 0.8) inpatient visits, and 0.5 (SD = 1.5) ED visits. The most common diagnoses were for circulatory or respiratory disease: of the 62,892 ED visits made over the study period, 49,364 (78%) were for circulatory or respiratory disease concerns, as were 30,325 (90%) of inpatient visits.

## $PM_{2.5}$ exposure

Mean daily wildfire PM2.5 concentration by ZCTA grouping throughout the study period was 0.22 $\mu g/m^3$ (SD = 2.67) (Figure 2b), since most groupings on most days (85% of days) had 0 wildfire $PM_{2.5}$, while the maximum wildfire PM2.5 concentration was 551.53 $\mu g/m^3$. On the 366 days (23%) when study area wildfire $PM_{2.5}$ was non-zero, the mean concentration in groupings with non-zero measurements was 5.6 $\mu g/m^3$ (SD = 12.1). On days where wildfire PM $_{2.5}$ exceeded USEPA limits, in ZCTA groupings over the limit, wildfire $PM_{2.5}$ made up 91% of total $PM_{2.5}$.

In adjusted negative binomial models, a daily 10 $\mu g/m^3$ increase in wildfire $PM_{2.5}$ was associated with a decrease in risk of outpatient visits one day later (RR = 0.96, 95% CI: 0.94, 0.99), but increases on four of the five subsequent days (Table 1a). Wildfire $PM_{2.5}$ levels were not associated with the count of all-cause ED or inpatient visits or ED or inpatient visits for cardiorespiratory concerns.

In our additional analysis examining weekly wildfire PM2.5 levels lagged up to two weeks, a 10 $\mu g/m^3$ increase in weekly $PM_{2.5}$ concentration was associated with a same-week increase in outpatient visits (RR = 1.10, 95% CI: 1.04, 1.17), consistent with the daily outpatient visit model. Additionally, there were increases in weekly outpatient visits one and two weeks later (Table 1b). Weekly $PM_{2.5}$ levels were not associated with the frequency of any other visits.

## Proximity to wildfire

There were 54 ZCTAs (9%) within 20 km of the Woolsey Fire boundary, which we considered exposed to the fire. Despite the comparatively small size of the Getty Fire (~3 $km^2$ vs ~400 $km^2$), 98 ZCTAs (17%) met our exposure definition, as the Getty Fire was closer to population centers. We estimated that 20 and 21 ZCTAs were evacuation exposed during the Woolsey and Getty fires, respectively. However, all evacuation exposed ZCTAs were also within 20km of the fire boundaries, meaning that the evacuation exposed ZCTAs were a subset of the wildfire proximate ZCTAs in both cases.

### Woolsey Fire proximity and evacuation exposure

During the Woolsey Fire, the frequency of all types of visits increased by 15 to 22% across the whole study area, except outpatient visits, which remained the same. Woolsey Fire proximity during the fire was associated with decreased outpatient visits, and increased inpatient admissions for cardiorespiratory disease (Figure 3). We observed similar associations between Woolsey Fire evacuation exposure and healthcare visits with elevated visit counts of all types of healthcare visits in ZCTAs evacuated during the fire, and during the fire, the frequency of all types of visits increased throughout the study area, except for outpatient visits (Figure 3). Evacuation from the Woolsey Fire was also associated with increased inpatient admissions for cardiorespiratory disease (Figure 3).

### Getty Fire proximity and evacuation exposure

During the Getty Fire, outpatient visits, ED visits, and ED visits for cardiorespiratory problems increased across the entire study area. We observed reduced risks of all visits types among proximity exposed ZCTAs during the Getty Fire, but confidence intervals were very wide (Figure 3). We observed similar, if somewhat attenuated, associations among evacuation exposed ZCTAs.

None of our results were sensitive to spline flexibility.

## Discussion

Using electronic health data on 236,732 Kaiser Permanente DME patients from 2016-2020, we found that an increase in wildfire $PM_{2.5}$ concentration was associated with next-day decreases in outpatient visits and increases in outpatient visits up to two weeks later. Increases in wildfire $PM_{2.5}$ were not associated with the frequency of ED or inpatient visits. Residential proximity to the large Woolsey Fire was also associated with fewer all-cause outpatient visits, as well as more cardiorespiratory inpatient visits, and evacuation from the Woolsey Fire was associated with increased cardiorespiratory inpatient visits. Our study was unique in that we included inpatient, ED, and outpatient visits, evaluated healthcare utilization among DME users, a group hypothesized to be susceptible to disaster and wildfire smoke exposures, and examined residence near a wildfire or an evacuation zone.

The literature describes a strong relationship between wildfire smoke exposure and cardiorespiratory health.[20] Large studies measure this association through healthcare utilization and have found increased risk of hospital admissions and ED visits for cardiorespiratory outcomes following wildfire $PM_{2.5}$, $PM_{10}$, or general smoke exposure in the U.S., Canada, Australia, and Brazil.[50–55] Fewer studies have examined wildfire PM2.5 exposure in vulnerable populations.[15,56] Of studies examining older adults, all have reported associations between smoke exposure and same or next-day increased inpatient and ED visit frequency[50,54,57,58] and while some studies find older adults at elevated risk compared to younger adults[16,52,57] others found no difference.[26,50] Surprisingly, we observed no association between wildfire $PM_{2.5}$ and ED or inpatient visits. We hypothesized that older adult DME users would be particularly susceptible to wildfire $PM_{2.5}$ due to probable high prevalence of underlying cardiorespiratory disease.[29] The observed null association between wildfire $PM_{2.5}$ and ED or inpatient visits may indicate that DME users, especially those vulnerable to smoke, may take precautions to protect themselves from effects described in other studies or study limitations may obscure associations between smoke and more urgent healthcare use.

Limited studies have assessed outpatient care utilization during smoke exposure and most have focused on outpatient visits for respiratory concerns, reporting increases during smoke exposure.[50,59–62] None of those studies examined all-cause outpatient care use. Hutchinson et al. 2018 simultaneously reported decreases in all-cause outpatient visits during smoke exposure and increases in visits for respiratory concerns only, during a five-day period following smoke exposure. Similarly, Henderson et al. 2011 found increased physician visits for asthma and all-respiratory outcomes related to same-day wildfire smoke exposure but no increase in physician visits for cardiovascular disease. We observed an initial next-day decrease in all-cause outpatient visits, and then a positive association between wildfire $PM_{2.5}$ and outpatient visits among DME users for the two weeks following exposure. These findings are consistent with much of the literature.

Few studies have evaluated proximity to wildfire boundaries or wildfire evacuation as risk factors for healthcare utilization or adverse health outcomes.[63–65] Proximity to wildfires can affect health through a stress pathway, on top of risks related to smoke exposure. Qualitative studies emphasize this point, and several have documented the immense stress experienced by those displaced by wildfire.[7,8,41] After the 2014 Canadian Northwest Territory wildfires, one interviewee said: “Well, it took a toll on me because being stressed out from the fires and never knowing when we had to leave to be evacuated we didn’t know if we were going to come home to a community or to our houses.”[28] Agyapong et al. 2021 estimated the likely prevalence of post-traumatic stress disorder among Canadian Fort McMurray wildfire survivors at 12.8%, twice the baseline population prevalence.[66] We attempted to assess this proximity/evacuation pathway for two major fires in our study area using a difference-in-differences analysis. We found no association between exposure and healthcare visits during the Getty Fire. However, during the Woolsey Fire, we observed an increase in cardiorespiratory inpatient visits and a decrease in all-cause outpatient visits with both fire proximity and evacuation. The 400 $km^2$ Woolsey Fire, which caused \$3 billion in damages,[67] was much larger than the 3 $km^2$ Getty Fire, which destroyed 10 homes,[35] that null associations between Getty proximity exposure and all visit types could be due to its smaller size; it may have not been large enough to produce a detectable effect in visit changes. A larger analysis examining several wildfires, rather than two, could be informative.

Study limitations could have influenced our results. First, we only had access to data on visits to Kaiser Permanente clinics and hospitals made by Kaiser members using DME. These patients would be highly motivated to seek care at Kaiser, given their membership status, however they may have sought urgent care at other clinics or hospitals. Such alternate utilization would have produced artificially reduced visit counts, especially for inpatient and emergency visits. If patients sought care at other clinics only during wildfires (whether during evacuations or while a fire was burning nearby) this could have biased association estimates towards the null.

Second, all visits were infrequent over the study period. Inpatient and ED visits were much less frequent over the study period than outpatient visits. All models may have been underpowered to detect changes in these visits. In particular, during the Woolsey Fire, we observed decreased outpatient visits in ZCTAs proximate to the fire, but we detected only a statistically insignificant decrease in outpatient visits in the subset of proximate ZCTAs evacuated from the fire. This is likely due to sample size.

Third, we did not assess differences in healthcare use by type of DME or stratify by age group or sex beyond limiting our study population to those age 45 or older. Excluding younger people excluded most breast pump users, a generally healthy subpopulation who constitute 30% of DME users of all ages at KPSC.[30] Subgroups such as those using ventilators or those using breast pumps likely have vastly different health needs and outcomes. We chose to focus on DME users aged 45 and older who were likely the most susceptible to wildfire. However, subgroups in our study may also have differing needs and outcomes, which we did not examine.

Lastly, as in any observational study, residual confounding could affect our results. We attempted to account for residual spatial confounding by including a set of ZCTA-level covariates that measured different facets of socioeconomic status.

# Tables and Figures

**Table 1a:** Risk ratio and 95% confidence intervals from a negative binomial model[a] assessing the association between daily wildfire $PM_{2.5}$ and healthcare utilization among KPSC DME users, daily lags.

| | **Risk ratios and [95% CI] for 10$\mu g/m^3$ increase in wildfire $PM_{2.5}$** | | | | | | |
|---|---|---|---|---|---|---|---|
| **Outcome** | **lag 0 days** | **lag 1 day** | **lag 2 days** | **lag 3 days** | **lag 4 days** | **lag 5 days** | **lag 6 days** |
| All-cause outpatient | 0.98 [0.96, 1.01] | 0.96 [0.94, 0.99] | 1.03 [1, 1.06] | 1.08 [1.05, 1.11] | 0.98 [0.95, 1.02] | 1.07 [1.04, 1.1] | 1.12 [1.09, 1.16] |
| All-cause inpatient | 0.94 [0.84, 1.04] | 1.01 [0.93, 1.1] | 0.95 [0.84, 1.08] | 0.87 [0.76, 1] | 0.98 [0.87, 1.12] | 0.93 [0.81, 1.06] | 1.02 [0.89, 1.16] |
| All-cause ED | 0.97 [0.91, 1.04] | 1.02 [0.96, 1.08] | 0.98 [0.89, 1.07] | 0.96 [0.88, 1.06] | 0.95 [0.86, 1.04] | 1.03 [0.93, 1.13] | 0.92 [0.82, 1.02] |
| Inpatient: cardiorespiratory concerns | 0.91 [0.81, 1.02] | 1.03 [0.95, 1.12] | 0.93 [0.82, 1.07] | 0.91 [0.79, 1.05] | 0.97 [0.85, 1.1] | 0.91 [0.79, 1.05] | 0.99 [0.86, 1.14] |
| ED: cardiorespiratory concerns | 0.99 [0.92, 1.07] | 0.99 [0.91, 1.08] | 0.96 [0.87, 1.07] | 0.99 [0.89, 1.1] | 0.92 [0.83, 1.03] | 1.01 [0.91, 1.13] | 0.89 [0.79, 1.01] |

[a] Negative binomial models included fixed effects for wildfire $PM_{2.5}$ lags 0-7 days, controlled for temperature, non-wildfire $PM_{2.5}$, and time effects. We added a fixed effect to account for fewer visits on weekend days, and an offset to account for exposed population. We also included fixed effects for a set of ZCTA-level socioeconomic variables: median household income, home ownership (% homes occupied by owner), poverty (percent households below threshold income), age structure (percent of population under 5, 5-19, 20-64, and 65+ years), and racial/ethnic composition (percent Hispanic, percent non-Hispanic white, percent non-Hispanic Black).

**Table 1b**: Risk ratio and 95% confidence intervals from a negative binomial model[a] assessing the association between daily wildfire $PM_{2.5}$ and healthcare utilization among KPSC DME users, weekly lags.

| | **Risk ratios and [95% CI] for 10$\mu g/m^3$ increase in wildfire $PM_{2.5}$** | | |
|---|---|---|---|
| **Outcome** | **lag 0 weeks** | **lag 1 week** | **lag 2 weeks** |
| All-cause outpatient | 1.10 [1.04, 1.17] | 1.04 [1.00, 1.09] | 1.05 [1.02, 1.09] |
| All-cause inpatient | 1.01 [0.84, 1.20] | 1.08 [0.94, 1.23] | 0.99 [0.85, 1.15] |
| All-cause ED | 1.03 [0.90, 1.19] | 0.99 [0.88, 1.11] | 1.02 [0.92, 1.14] |
| Inpatient: cardiorespiratory concerns | 0.94 [0.78, 1.12] | 1.10 [0.96, 1.27] | 0.98 [0.85, 1.15] |
| ED: cardiorespiratory concerns | 1.07 [0.92, 1.26] | 0.96 [0.84, 1.10] | 1.02 [0.91, 1.15] |

[a]Negative binomial models included fixed effects for weekly mean wildfire $PM_{2.5}$ lags 0-2 week, controlled for temperature, non-wildfire $PM_{2.5}$, and time effects, and added an offset to account for exposed population. We also included fixed effects for a set of ZCTA-level socioeconomic variables: median household income, home ownership (% homes occupied by owner), poverty (percent households below threshold income), age structure (percent of population under 5, 5-19, 20-64, and 65+ years), and racial/ethnic composition (percent Hispanic, percent non-Hispanic white, percent non-Hispanic Black).

Figure 1:

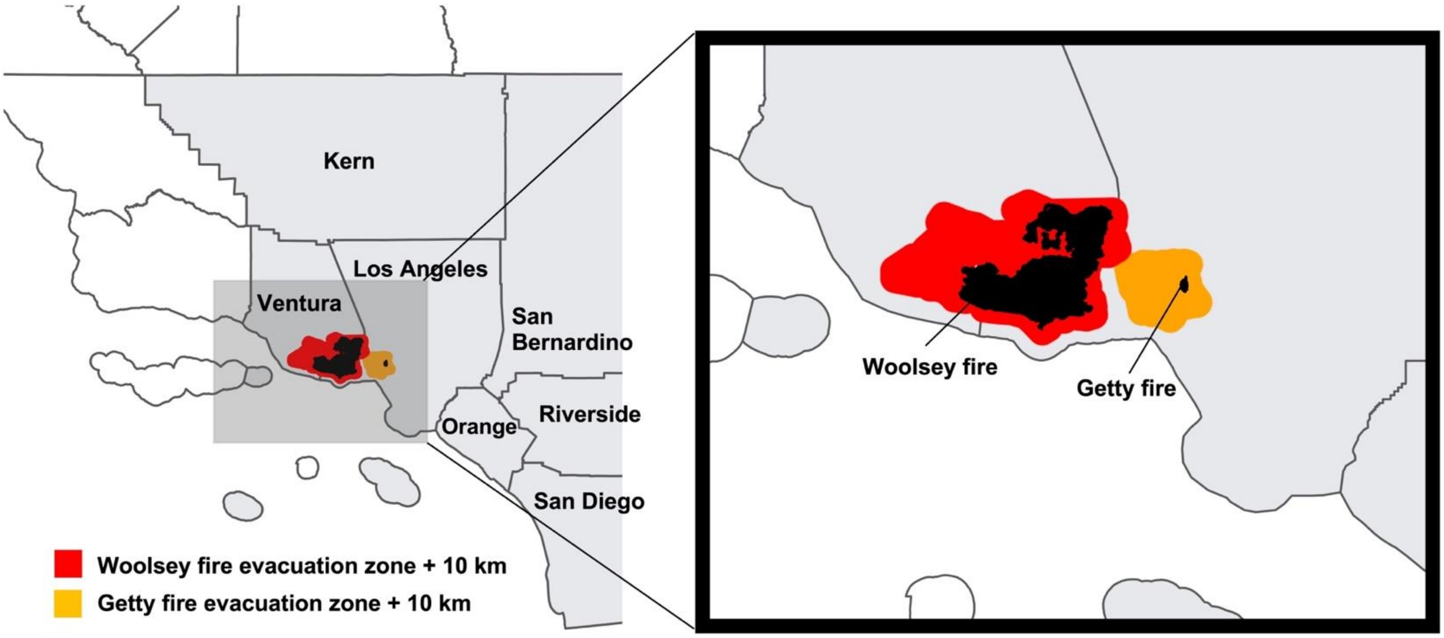


Figure 1: Map of Southern California study area, shaded in grey, with counties labelled in black. Woolsey and Getty fire burn areas are shaded in black.

Figure 2a: Daily mean non-wildfire $PM_{2.5}$ concentrations by study area county from January 2016 – March 2020. Measurements are in $\mu g/m^3$. Dotted lines represent the USEPA recommended 35 $\mu g/m^3$ daily limit. Colored time periods represent measurements made while a wildfire was burning.

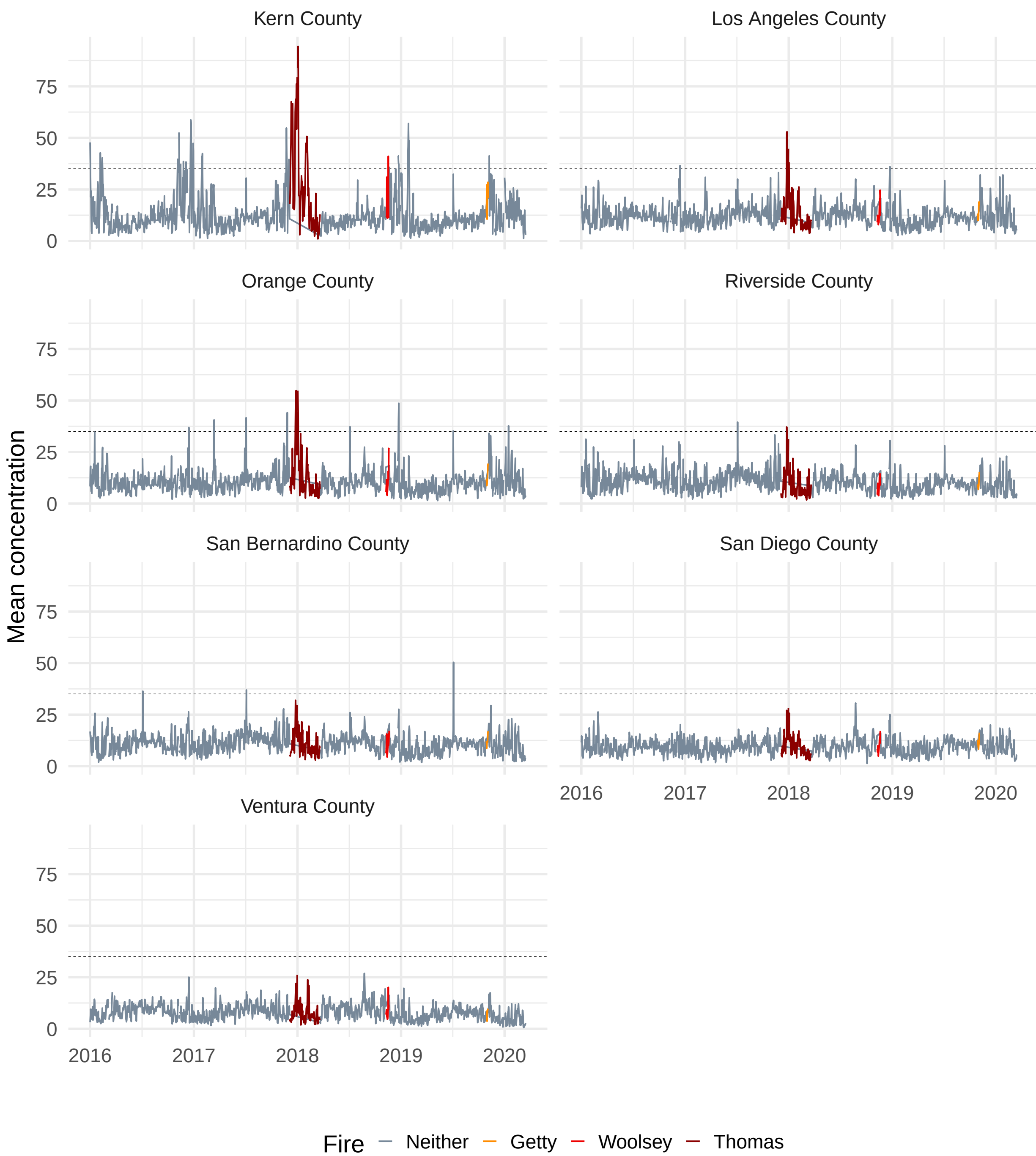

Figure 2b: Daily mean wildfire $PM_{2.5}$ concentrations by study area county from January 2016 – March 2020. Measurements are in $\mu g/m^3$. Dotted lines represent the USEPA recommended 35 $\mu g/m^3$ daily limit. Colored time periods represent measurements made while a wildfire was burning.

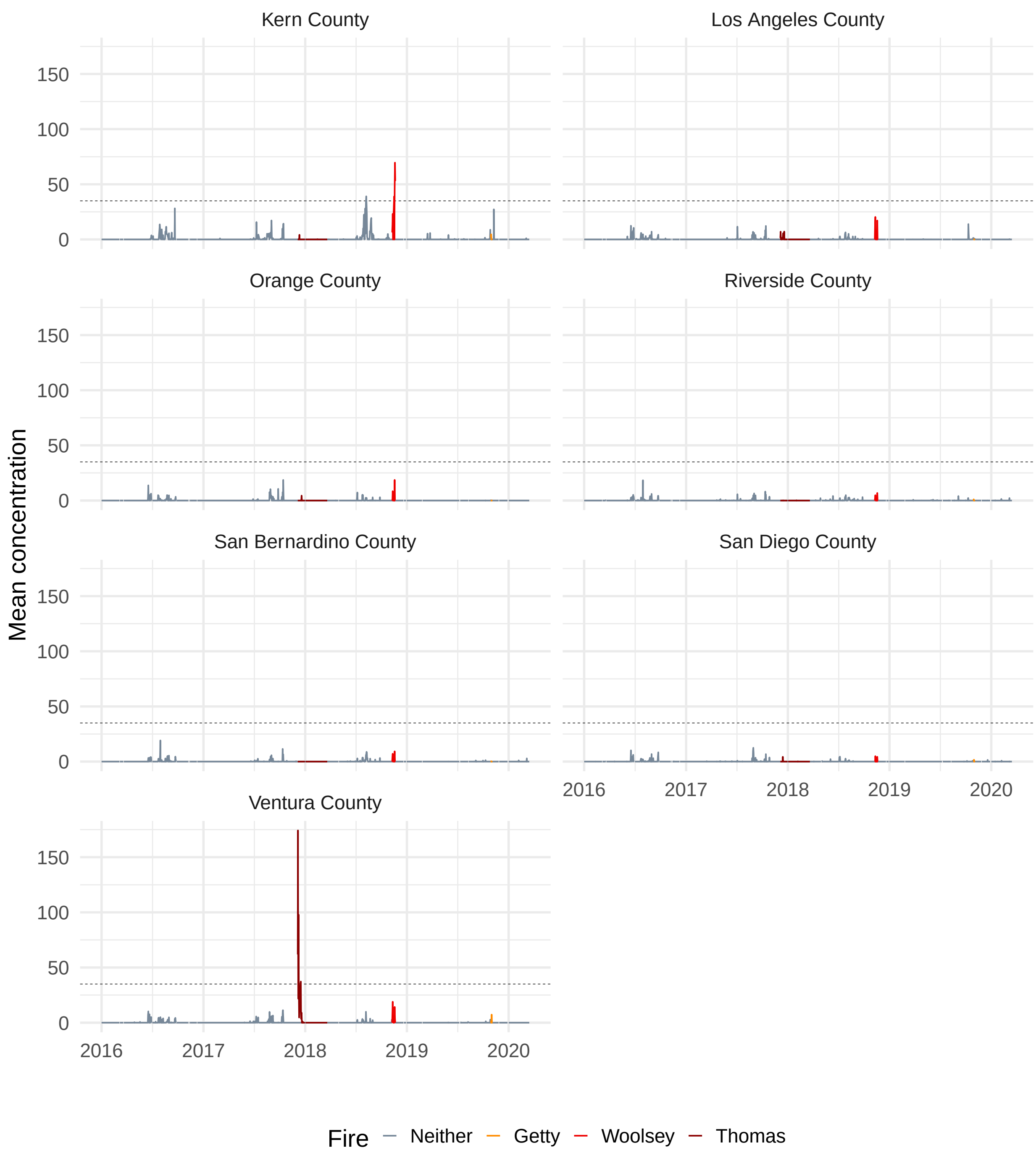

Figure 3: We used negative binomial regression to evaluate the effect of wildfire evacuation or proximity during an active fire. The DID estimators subtracted the change in visit frequency during a fire among ZCTAs far from the fire or evacuation zone (difference 1) from the change in visit frequency during a fire among ZCTAs exposed to the fire or evacuation zone (difference 2). We controlled for time effects, temperature, and non-wildfire $PM_{2.5}$, and added an offset for the size of the exposed population.

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