**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 PM2.5 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 PM2.5 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 PM2.5 concentration (per 10 𝜇𝑔/𝑚3) 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 PM2.5 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 = 1.45, 95% CI: 0.99, 2.12, evacuation RR = 1.72, 95% CI: 1.00, 2.96). 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 decades1-5. Development in the wildland-urban interface has placed more communities in the path of these increasingly frequent disasters6. Immediate impacts of wildfire, such as evacuations, power outages, and destruction of infrastructure cause trauma, stress, financial strain, and physical injury in affected communities7,8. Simultaneously, 70% of the US population is exposed to wildfire smoke annually9-11[[1]](#endnote-1)9-11.

Among other hazardous components, wildfire smoke contains fine particulate matter (PM2.5). Of PM2.5 sources, wildfire PM2.5 may be particularly harmful because it consists of more organic and elemental carbo[[2]](#endnote-2)n12-14. It also constitutes most extreme PM2.5 exposure in California, accounting for 71% of total PM2.5 on days that exceed US Environmental Protection Agency (USEPA) annual standard of 12 𝜇𝑔/𝑚3 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 exacerbation15-17, increases in ED and inpatient visits related to cardiorespiratory disease18-21, and increased mortality risk22-24.

Several studies have documented the health effects of stress, evacuation, property destruction, or injury due to wildfire disasters7,8,21,25-31. We seek to expand on this literature. We hypothesize that residential proximity to wildfire, and evacuations due to wildfire, could influence health outcomes primarily through stress and possibly operate differently than wildfire PM2.5 exposure. Residents living near wildfires are exposed to smoke, which in addition to biological effects can cause substantial worry32. Proximate residents also experience the disruption of usual community activities, and face threat of injury, evacuation, or longer-term displacement. Evacuation may also disrupt access to healthcare, possibly resulting in a temporary reduction in utilization33.

People who use durable medical equipment (DME) may be particularly vulnerable to wildfire PM2.5 exposure and stress from wildfire proximity or evacuation. DME use is common among older adults and is associated with respiratory illness and other disabilities29. Prevalence of DME rentals at Kaiser Permanente Southern California (KPSC) increased from 2008-2018, with the highest prevalence among older adults30. DME types included bilevel positive airway pressure (BiPAP) machines, enteral feeding machines, infusion pumps, oxygen equipment, suction pumps, ventilators, and wheelchairs30.

This group may face unique challenges during wildfire events. The association between wildfire smoke exposure and respiratory and cardiovascular disease outcomes has been stronger among older adults compared to younger populations16,31. Further, people using DME may have co-occurring medical conditions such as cardiovascular disease that make them more vulnerable wildfire PM2.5 and wildfire-related stressors like threatened or actual evacuation. Limited mobility or need for electricity access may result in increased difficulty evacuating disaster zones30,34.

Here, we use 2016-2020 KPSC electronic health records of older adults using DME–likely a medically and socially vulnerable group–from seven Southern California counties to examine the relationship between wildfire exposure and healthcare utilization. We evaluate exposure to wildfire via (1) wildfire PM2.5 concentrations, and (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 400km2 Woolsey Fire, which burned from November 8-21, 2018 in Los Angeles and Ventura counties, displacing 295,000 people and killing three35,36, and the 3km2 Getty Fire, which necessitated evacuations in densely populated Los Angeles, and burned from October 28-November 5, 201936,37.

**Methods**

**Study population**

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. KPSC patients represent the underlying population in the region, except for slight under-representation of individuals living in the highest and lowest SES communities. We excluded younger DME renters in order to focus on socially and medically vulnerable older adults, but also to exclude breast pump users, a healthy subgroup of the otherwise vulnerable DME using population, who we did not hypothesize to be disproportionately vulnerable to wildfire exposure. Electronic health record data included each patient’s Zip Code Tabulation Area (ZCTA) of residence. We obtained daily counts of healthcare visits–not necessarily related to DME use–by this population by residential ZCTA 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 km2 in California36,38, 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, since the data were fully de-identified before researchers at Columbia received them.

**Exposure Definition**

**Wildfire PM2.5**

We measured wildfire smoke exposure by estimating daily wildfire and non-wildfire PM2.5 concentrations at the ZCTA level using a multistage approach described elsewhere and in the supplemental digital content39.

We calculated daily wildfire and non-wildfire PM2.5 by averaging concentrations across the higher-level spatial groupings of several ZCTAs based on spatial proximity (hereafter ‘ZCTA groupings’; grouping method described in the eAppendix).

**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 km2 of land, making it particularly destructive35,36. 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 Angeles36,37.

Notably, The Thomas Fire also burned over 1100 km2 during our study period40. 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, since very few participants would have been exposed to it. Still, smoke from this fire contributed substantially to wildfire PM2.5 in Ventura County in December 2017, and therefore was included in our PM2.5 analyses (Figure 2b).

We obtained shapefiles of the total areas burned during the Getty and Woolsey fires from the CALFIRE Fire and Resource Assessment Program41. These perimeters represented the approximately the maximum burned areas of each fire40 and we used them to define exposure. We considered ZCTAs exposed if their boundary was within 20km of a final fire perimeter on days that a fire was active. US-based studies have evaluated exposure to wildfire disasters in different ways, including self-reported impact42, wildfire damage to own home43, evacuation from own home44,45, residence in a community where structures burned46, residence in a county where a wildfire burned47, and residential proximity to a wildfire48. We selected the Getty and Woolsey wildfires a priori, then linked exposure via proximity to the wildfire boundaries, selecting a distance of 20km as one that could elicit a stress response; prior studies have found impacts on wellbeing and mental health at similar distances49.

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 QGIS50 (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 definition7,8,51.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. These visits were not necessarily related to DME use. We identified cause-specific visit counts using *International Classification of Diseases 10* codes I00-I99 (circulatory) and J00-J99 (respiratory). 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, and to increase statistical power, 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 week18–21. To evaluate a lagged temporal 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. We aggregated to the weekly level because we used last recorded fire boundaries and last recorded evacuation zones rather than daily PM2.5 concentrations as we had available for our air pollution analyses. By aggregating, we also removed weekend-weekday patterns in outpatient visits, increased power, and reduced zero inflation. We considered a week exposed if the Woolsey or Getty fire burned any day that week.

**Analysis**

**Wildfire PM2.5**

To evaluate the relationship between daily wildfire PM2.5 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 exposures52. We examined the autocorrelation of wildfire PM2.5 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 PM2.5 concentrations increased dramatically on certain days, then decreased just as quickly (Figure 2b). We therefore created unconstrained models, including separate terms for wildfire PM2.5 lags 0-7 days. We also performed an additional analysis examining weekly wildfire PM2.5 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 utilization53 and

wildfire54, using daily temperature data from the PRISM Climate Group55. 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 PM2.5, since

non-wildfire PM 2.5 concentrations were high during the study period: mean daily non-wildfire PM2.5 by grouping was 11.0 𝜇𝑔/𝑚3 (SD = 6.69), just under the annual USEPA National Ambient Air Quality Standard of 12 μg/m3 (Figure 2a). We also added a fixed effect for weekends to the outpatient visits model, accounting for fewer visits on weekend days.

We controlled 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 ACS56 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 the association between proximity to and evacuation exposure related to wildfire and weekly ZCTA-level healthcare visit counts, we used a difference-in-differences (DID) analysis with negative binomial regression. We evaluated relationships separately for each fire, for evacuation and proximity, and for each type of healthcare visit. The DID estimators subtracted the change in visit frequency when the Getty or Woolsey Fire was burning versus not burning among control ZCTAs (difference 1) from the change in visit frequency when the Getty or Woolsey Fire was burning versus not burning 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 due to exposure to fires, we excluded certain observations from specific ZCTAs from the control pool. If a ZCTA was exposed (i.e., boundary within 20km) to the Getty and Woolsey Fires or exposed to any other large fire that was declared a disaster by FEMA, burned a structure, or killed someone during the study period, we excluded observations from that ZCTA after the date the Getty, Woolsey, or other fire ignited. We used a CALFIRE fire perimeter data38 to identify all fires that met these criteria.

As in the wildfire PM2.5 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 PM2.5 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 also tested all models for sensitivity to the size of the buffer around the wildfire perimeters and evacuation zones, by re-running analyses with a 30km buffer instead of a 20km buffer, expanding the exposed zone to include people further away from the fire or evacuation boundary. We conducted all analyses in R57, using the mgcv package58. 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.

**PM2.5 exposure**

Mean daily wildfire PM2.5 concentration by ZCTA grouping throughout the study period was 0.22 𝜇𝑔/𝑚3 (SD = 2.67) (Figure 2b), since most groupings on most days (85% of days) had 0 wildfire PM2.5, while the maximum wildfire PM2.5 concentration was 551.53 𝜇𝑔/𝑚3 . On the 366 days (23%) when study area wildfire PM2.5 was non-zero, the mean concentration in groupings with non-zero measurements was 5.6 𝜇𝑔/𝑚3 (SD = 12.1). On days where wildfire PM 2.5 exceeded USEPA air quality standards, in ZCTA groupings over the standard, wildfire PM2.5 made up 91% of total PM2.5.

In adjusted negative binomial models, a daily 10 𝜇𝑔/𝑚3 increase in wildfire PM2.5 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 PM2.5 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 increase in weekly PM2.5 concentration was associated with a next-week increase in outpatient visits (RR = 1.04, 95% CI: 1.00, 1.09), consistent with the daily outpatient visit model. Additionally, there were increases in weekly outpatient visits two weeks later (Table 1b). We did not interpret the same-week coefficient due to issues with temporality – our outcome may have preceded the exposure. Weekly wildfire PM2.5 was 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 km2 vs ~400 km2), 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**

Residence in a ZCTA located within 20km of the Woolsey Fire boundary during the fire was associated with increased inpatient admissions for cardiorespiratory disease compared residence outside of it (RR = 1.45, 95% CI: 0.99, 2.12), and associated with decreased all-cause outpatient visits compared to residence outside of it (RR = 0.89, 95% CI: 0.79, 1.00), though the confidence intervals were wide (Figure 3). We observed similar associations, with narrower confidence intervals, between Woolsey Fire evacuation exposure and healthcare visits. Residence in a ZCTA located in an evacuation zone of the Woolsey Fire during the fire was also associated with decreased all-cause outpatient and increased inpatient admissions for cardiorespiratory disease visits compared to residence outside of it (RR = 0.86, 95% CI: 0.72, 1.03, RR = 1.72, 95% CI: 1.00, 2.96, respectively) (Figure 3).

**Getty Fire proximity and evacuation exposure**

We observed no association between Getty Fire proximity during the fire and risk of all visits types (Figure 3). Residence within an evacuation zone plus 10km was associated with reduced risk of all types of visits, though confidence intervals were very wide (Figure 3).

None of our results were sensitive to spline flexibility or the size of the buffer around exposures. Visual inspection of model residuals and Moran’s I results indicated that our model residuals were not exhibit spatial autocorrelation (plots included in the eAppendix).

**Discussion**

Using electronic health data describing 236,732 Kaiser Permanente DME-using patients from 2016-2020, we found that an increase in wildfire PM2.5 concentration was associated with brief (next-day) decreases in all-cause outpatient visits but increases in all-cause outpatient visits up to two weeks later. Increases in wildfire PM2.5 were not associated with the frequency of ED or inpatient visits among DME users. Residential proximity of DME users to the large Woolsey Fire was also associated with fewer all-cause outpatient visits, as well as more cardiorespiratory inpatient visits, but not with other visit types. Results for Woolsey Fire evacuation exposure were similar. Getty Fire evacuation or proximity was not associated with frequency of any kind of healthcare visit. Our study was unique in that we evaluated healthcare utilization among DME users, a group hypothesized to be susceptible to disaster and wildfire smoke exposures, included inpatient, ED, and outpatient visits, and examined residence near a wildfire or an evacuation zone in addition to wildfire PM2.5 exposure.

The literature describes a strong relationship between wildfire smoke exposure and respiratory health20, and a strong relationship between PM 2.5 exposure and cardiovascular health59, though the relationship between wildfire PM2.5 and cardiovascular health is still being characterized. Large studies measure this association through healthcare utilization and have found increased risk of hospital admissions and ED visits for cardiorespiratory outcomes following wildfire PM2.5, PM10, or general smoke exposure in the U.S., Canada, Australia, and Brazil60–65. Fewer studies have examined wildfire PM2.5 exposure in vulnerable populations15,66. Of studies examining older adults, all have reported associations between smoke exposure and same or next-day increased inpatient and ED visit frequency60,64,67,68 and while some studies find older adults at elevated risk compared to younger adults16,62,67 others found no difference26,60. Surprisingly, we observed no association between wildfire PM2.5 and ED or inpatient visits among DME users. We hypothesized that older adult DME users would be particularly susceptible to wildfire PM2.5 due to probable high prevalence of underlying cardiorespiratory disease29. The observed null association between wildfire PM2.5 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 exposure60,69–72. 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. In models with daily lags, we observed an initial same-day and next-day decrease in all-cause outpatient visits, and then a positive association between wildfire PM2.5 and all-cause outpatient visits among DME users for the week following exposure. In models with weekly lags, we observed increased outpatient visits in the two weeks following exposure, suggesting that there is overall an increase in all-cause outpatient visits among DME users following wildfire PM2.5 exposure. These findings are consistent with much of the literature in that they indicate increased healthcare utilization following smoke exposure. Very few prior studies have evaluated lags of short-term exposure to wildfire PM2.5 beyond 7 days78, but our results indicate that outpatient visits among DME users remained elevated for up to two weeks.

Few studies have evaluated proximity to wildfire boundaries or wildfire evacuation as risk factors for healthcare utilization or adverse health outcomes73–75. 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 wildfire7,8,51. 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 prevalence76. 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 among DME users. The 400 km2 Woolsey Fire, which caused $3 billion in damages,77 was much larger than the 3 km2 Getty Fire, which destroyed 10 homes37, 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 identified KPSC members who rented DME in the year prior to October 29, 2019. This meant that some study participants may not have been using DME at the time of wildfire exposure or healthcare visit but were nonetheless likely socially or medically vulnerable. KPSC 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, we lacked individual-level information on participants. Therefore, we did not know if patients sought care for DME-related issues and only used prior DME use as a vulnerability metric. We also were not able to 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 KPSC30. 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 overall aged 45 and older who were likely the most susceptible to wildfire. However, users of specific types of DME, such as oxygen concentrators, or DME users of different ages, such as those over 75 years, may have unique needs and differing outcomes; future research may wish to examine these sub-groups in detail.

Third, days with 0 visits made by patients living in a spatial grouping were common. Inpatient and ED visits were much less frequent over the study period (both mean = 0.1 daily visits) than outpatient visits (mean = 2.5 daily visits). All models may have been underpowered to detect visit changes. For example, during the Woolsey Fire, we observed decreased outpatient visits in ZCTAs proximate to the fire and among evacuation exposed ZCTAs but, for both, confidence intervals were wide, likely due to sample size.

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.

**Conclusion**

As wildfires become more frequent and severe with climate change, we must understand how they affect both proximate populations and those exposed to wildfire PM2.5. Protecting vulnerable populations that may be harmed by exposures which others can avoid or endure is essential. More work is needed to understand we can best support those affected by smoke, fire, and evacuation.

# Tables and Figures

**Table 1a:** Risk ratio and 95% confidence intervals from a negative binomial modela assessing the association between daily wildfire PM2.5 and healthcare utilization among KPSC DME users, daily lags.

|  | **Risk ratios and [95% CI] for 10increase in wildfire PM2.5** | | | | | | |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **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 PM2.5 lags 0-7 days, controlled for temperature, non-wildfire PM2.5, 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 modela assessing the association between daily wildfire PM2.5 and healthcare utilization among KPSC DME users, weekly lags.

| **Risk ratios and [95% CI] for 10increase in wildfire PM2.5** | | |
| --- | --- | --- |
| **Outcome** | **lag 1 week** | **lag 2 weeks** | |
| All-cause outpatient | 1.04 [1.00, 1.09] | 1.05 [1.02, 1.09] | |
| All-cause inpatient | 1.08 [0.94, 1.23] | 0.99 [0.85, 1.15] | |
| All-cause ED | 0.99 [0.88, 1.11] | 1.02 [0.92, 1.14] | |
| Inpatient: cardiorespiratory concerns | 1.10 [0.96, 1.27] | 0.98 [0.85, 1.15] | |
| ED: cardiorespiratory concerns | 0.96 [0.84, 1.10] | 1.02 [0.91, 1.15] | |

aNegative binomial models included fixed effects for weekly mean wildfire PM2.5 lags 0-2 weeks, controlled for temperature, non-wildfire PM2.5, 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).

*Diagram

Description automatically generated*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 PM2.5 concentrations by study area county from January 2016 – March 2020. Measurements are in . Dotted lines represent the USEPA 35 standard. Colored time periods represent measurements made while a wildfire was burning.

Figure 2b: Daily mean wildfire PM2.5 concentrations by study area county from January 2016 – March 2020. Measurements are in . Dotted lines represent the USEPA 35 standard. 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 when the Getty or Woolsey Fire was burning versus not burning among control ZCTAs (difference 1) from the change in visit frequency when the Getty or Woolsey Fire was burning versus not burning among ZCTAs exposed to the fire or evacuation zone (difference 2).We controlled for time effects, temperature, and non-wildfire PM2.5, and added an offset for the size of the exposed population.



Cardiorespiratory emergency visits

Cardiorespiratory inpatient visits

All-cause emergency visits

All-cause

inpatient visits

All-cause

outpatient visits



Cardiorespiratory emergency visits

Cardiorespiratory inpatient visits

All-cause emergency visits

All-cause

inpatient visits

All-cause

outpatient visits

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