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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 vulnerable to health effects from wildfire smoke, residence near wildfires, or residence in evacuation zones. To our knowledge, no studies have examined their healthcare utilization during wildfires.

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

Results: Among 236,732 DME users, 10 $\mu g/m^3$ increases in wildfire $PM_{2.5}$ concentration were associated with reduced rate (RR = 0.96, 95% CI: 0.94, 0.99) of all-cause outpatient visits one day after exposure and increased rate on 4 of 5 subsequent days (RR range 1.03–1.12). 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: Our results support the hypothesis that wildfire smoke or proximity interrupts DME users' routine outpatient care, via sheltering in place. However, wildfire exposures were also associated with increased urgent healthcare utilization in this vulnerable group.

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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.

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]. 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[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 $PM_{2.5}$ 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 emergency department (ED) and inpatient visits related to cardiorespiratory disease[18–21], and increased mortality risk[22–24].

Proximity to wildfire or residence in an evacuation zone may not only cause visible smoke exposure or extreme wildfire-related air pollution, it may also involve possible evacuation, community disruption, loss of access to community services and housing, power outages, and stress co-occurring with and resulting from these events.

People who use durable medical equipment (DME) 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]. Prevalence of DME rentals at Kaiser Permanente Southern California (KPSC) increased from 2008–2018, with the highest prevalence 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. The association between wildfire smoke exposure and respiratory and cardiovascular disease outcomes has may be stronger 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 wildfire $PM_{2.5}$ and wildfire-related stressors like threatened or actual evacuation. Limited mobility or need for electricity access may result in increased difficulty evacuating disaster zones[30,35].

Our study has two unique components. First, we focus on a potentially vulnerable population by using 2016–2020 KPSC electronic health records from seven Southern California counties to examine the relationship between wildfire exposure and healthcare utilization in people who use DME. Second, we evaluate exposure to wildfire via (1) wildfire $PM_{2.5}$ concentrations, and (2a) residential proximity to major active fires, and (2b) residence in an evacuated area. These proximity-based residential exposure estimates attempt to holistically assess the impact of wildfire exposure, including stress, rather than focusing only on air pollution. Our study period includes two major wildfire events in populated areas: the 400km^2 Woolsey Fire, which burned from November 8–21 2018 in Los Angeles and Ventura counties, displacing 295,000 people and killing three[36,37], and the 3km^2 Getty Fire, which necessitated evacuations in densely populated Los Angeles, and burned from October 28-November 5, 2019[37,38].

Methods

Study population

We used electronic health record data from KPSC to identify all individuals who were 45 or older as of October 28 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 socioeconomic status (SES) communities[39]. 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, whom 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 1 2016 to March 15 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[37,40], 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 $PM_{2.5}$—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 and in the supplemental digital content, in eMethods 1[40].

We calculated daily wildfire and non-wildfire $PM_{2.5}$ by averaging concentrations across the higher-level spatial groupings of several ZCTAs based on spatial proximity (hereafter 'ZCTA groupings'; grouping method described in eMethods 2, in the eAppendix).

Proximity to wildfire—To measure direct exposure to wildfire, we obtained data on the fire boundaries and evacuation zones of two disastrous Southern California wildfires – the Woolsey Fire and the Getty Fire. We chose these fires because they affected a substantial number of people in our study area, during the study period. The Woolsey Fire, which burned from November 8 2018 until November 21 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[36,37]. The Getty Fire, which ignited on October 28 2019 and burned until November 5th, 2019, was notable because it necessitated evacuations during its 9-day duration in densely populated Los Angeles[37,38].

Notably, The Thomas Fire also burned over 1100 km^2 during our study period[42]. 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 $PM_{2.5}$ in Ventura County in December 2017, and therefore was included in our $PM_{2.5}$ analyses (Figure 2).

We obtained shapefiles of the total areas burned during the Getty and Woolsey fires from the CALFIRE Fire and Resource Assessment Program[43]. These perimeters represented the approximately the maximum burned areas of each fire[42] 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 impact[44], wildfire damage to own home[45], evacuation from own home[46,47], residence in a community where structures burned[48], residence in a county where a wildfire burned[49], and residential proximity to a wildfire[50]. 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 distances[51].

Next, we created an evacuation exposure metric. GIS data on evacuation zones were not available for either fire. Therefore, we reviewed webpages (described in eMethods 3, in the eAppendix) containing maps of the evacuation zones and digitized boundaries around all areas ever evacuated during either fire in QGIS[52] (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[7,8,53]. We chose a 10km buffer rather than the previous 20km buffer because evacuation zones themselves can be large.

By measuring proximity to wildfire or residence in an evacuation zone, we aimed to capture a mixture of exposures, including possible visible smoke exposure or extreme wildfire-related air pollution, possible evacuation, community disruption, loss of access to community services and housing, power outages, and stress co-occurring with and resulting from these events. Though not all people living near a wildfire experience every component

of this mixture, we think the most important component is stress from the disaster. We have created a DAG (eFigure 1) describing this mixture.

Outcome Definition

We obtained daily counts of all-cause outpatient visits, all-cause emergency department (ED) visits, and all-cause inpatient admissions, as well as ED visits and inpatient admissions specifically for circulatory or respiratory disease outcomes made by KPSC members 45 and older who rented DME. Outpatient visits included both in-person and virtual synchronous visits (i.e., video or telephone visit with a provider), ED visits were those that terminated in the ED, and inpatient admissions consisted of all inpatient admissions (scheduled and unscheduled) as well as ED visits ending in an admission. Generally, outpatient visits are considered the lowest acuity, followed by ED visits, and inpatient visits are highest acuity. Recorded visits represent the universe of visits and 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 1 2016 to March 15 2020.

Daily visit counts by ZCTA were low and often zero [median outpatient visits = 1, interquartile range width (IQR_w) = 3, median ED and inpatient visits = 0, IQR_w = 0). For the wildfire $PM_{2.5}$ 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 week[18–21]. 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 eMethods 2, the eAppendix).

For analyses measuring residence near a fire on in an evacuation zone, 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 $PM_{2.5}$ concentrations as we had available for our air pollution. 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 $PM_{2.5}$—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[54]. 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 3). 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, ED, and inpatient visits, and ED and inpatient 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[55] and wildfire[56], using daily mean temperature data from the PRISM Climate Group[57]. We did not include any lags on temperature. 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 $PM_{2.5}$ by grouping was 11.0 $\mu g/m3$ (SD = 6.69), just under the annual USEPA National Ambient Air Quality Standard of 12 $\mu g/m^3$ (Figure 2). 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 ACS[58] 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 and 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 weekly 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 in eFigure 2 in the supplemental digital content.

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 data[40] to identify all fires that met these criteria.

As in the wildfire $PM_{2.5}$ models, we included offsets accounting for the population exposed and controlled for temperature with a penalized spline and non-wildfire $PM_{2.5}$ with a linear term. 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 a model describing residence proximate to a fire or in an evacuation zone, as we considered this part of our multifaceted exposure 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 R[59], using the mgcv package[60]. 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 = 0.5) ED visits, and 0.1 (SD = 0.4) inpatient visits per ZCTA grouping. There were on average 8 (SD = 8.9) outpatient visits per week per ZCTA, 0.5 (SD = 1.5) ED visits, and 0.2 (SD = 0.8) inpatient 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 $PM_{2.5}$ concentration by ZCTA grouping throughout the study period was 0.22 $\mu g/m^3$ (SD = 2.67) (Figure 2), since most groupings on most days (85% of days) had 0 wildfire $PM_{2.5}$, while the maximum wildfire $PM_{2.5}$ 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 air quality standards, in ZCTA groupings over the standard, 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 rate of outpatient visits 1 day later (RR = 0.96, 95% CI: 0.94, 0.99), but increases on four of the five subsequent days (RR range 1.03–1.12, Table 1). 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 $PM_{2.5}$ levels lagged up to 2 weeks, a 10 $\mu g/m^3$ increase in weekly wildfire $PM_{2.5}$ 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 2). We did not interpret the same-week coefficient due to issues with temporality – our outcome may have preceded the exposure. Weekly wildfire $PM_{2.5}$ was not associated with the frequency of any other visits.

In additional analyses examining ED and inpatient visits, we also observed an 8% increase in rate of inpatient visits and a 10% increase in rate of cardiorespiratory inpatient visits 1 week following a 10 $\mu g/m^3$ increase in weekly wildfire $PM_{2.5}$ concentration (Table 2). Daily lag estimates were unstable, possibly owing to smaller sample sizes for inpatient and cardiorespiratory inpatient visits (Table 1).

Proximity to wildfire

There were 54 ZCTAs (9%) within 20 km of the Woolsey Fire boundary. We considered residents of these ZCTAs 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 overlapped with evacuation zones during the Woolsey and Getty fires, respectively. However, all ZCTAs overlapping with evacuation zones were also within 20km of the fire boundaries, meaning that the 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 4). We observed similar associations, with wider 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), and was not associated with ED visit frequency (Figure 4). Detailed RRs for all visit types are outlined in eTable 1a and 1c.

Getty Fire proximity and evacuation exposure

We observed no difference in frequency for any visit type during the Getty Fire for those living within 20 km of the fire compared to those living further away (Figure 4). Residence within an evacuation zone plus 10km was associated with reduced rate of all types of visits, though confidence intervals were very wide (Figure 4). Detailed RRs for all visit types are outlined in eTable 1b and 1d.

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 eFigure 3, in the eAppendix).

Discussion

In this paper, we aimed to evaluate the relationship between daily wildfire $PM_{2.5}$ exposure, residence near a wildfire, and residence in an evacuation zone, and daily ZCTA grouping-level healthcare visit counts. Using electronic health data describing 236,732 Kaiser Permanente DME-using patients from 2016–2020, we found that an increase in wildfire $PM_{2.5}$ concentration was associated with brief (next-day) decreases in all-cause outpatient visits but increases in all-cause outpatient visits up to 2 weeks later in this population. Increases in wildfire $PM_{2.5}$ were not associated with the frequency of daily ED or inpatient visits among DME users. However, in sensitivity analyses of 1-week lags, we did find elevated 1-week lag RRs for inpatient visits (RR=1.08) and cardiorespiratory inpatient visits (RR=1.10). 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 $PM_{2.5}$ exposure.

The literature describes a strong relationship between wildfire smoke exposure and respiratory health[20], and a strong relationship between $PM_{2.5}$ exposure and cardiovascular health[61], though the relationship between wildfire $PM_{2.5}$ 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 $PM_{2.5}$, PM10, or general smoke exposure in the U.S., Canada, Australia, and Brazil[62–67]. Fewer studies have examined wildfire $PM_{2.5}$ exposure in vulnerable populations[15,68]. Of studies examining older adults, all have reported associations between smoke exposure and same or next-day increased inpatient and ED visit frequency[62,66,69,70] and while some studies find older adults at elevated risk compared to younger adults[16,64,69] others found no difference[26,62]. Surprisingly, we observed no association between wildfire $PM_{2.5}$ and ED or inpatient visits among DME users. 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[30]. 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 wildfire smoke exposure and most have focused on outpatient visits for respiratory concerns, reporting increases during smoke exposure[62,71–74]. None of those studies examined all-cause outpatient care use. Hutchinson et al. 2018[19] simultaneously reported decreases in all-cause outpatient visits during smoke exposure and increases in visits for respiratory concerns only, during a 5-day period following smoke exposure, suggesting that all or routine outpatient care may be disrupted, but respiratory care may be more needed and accessed during these

exposures. Similarly, Henderson et al. 2011[61] 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 $PM_{2.5}$ 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 2 weeks following exposure, suggesting that there is overall an increase in all-cause outpatient visits among DME users following wildfire $PM_{2.5}$ exposure. Very few prior studies have evaluated lags of short-term exposure to wildfire $PM_{2.5}$ beyond 7 days,[34] but our results indicate that outpatient visits among DME users remained elevated for up to 2 weeks. A decrease in healthcare utilization has been observed in previous studies of disaster-related exposures, including wildfires[75] and extreme storms[76]. Our findings are consistent with theories that wildfire smoke may disrupt care immediately[18,61], but at the same time exacerbate respiratory conditions leading to increased care use following smoke exposure among people (such as DME users) who have respiratory conditions.

Few studies have evaluated proximity to wildfire boundaries or wildfire evacuation as risk factors for healthcare utilization or adverse health outcomes[74,77,78]. 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[7,8,53]. 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[79]. 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 residential proximity to fire and residence in an evacuation among DME users. The 400 km^2 Woolsey Fire, which caused $3 billion in damages,[80] was much larger than the 3 km^2 Getty Fire, which destroyed 10 homes[39], 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. As in our discussion of wildfire $PM_{2.5}$ exposure, the Woolsey Fire may have decreased outpatient care as has been documented during other disaster scenarios,[75, 76] while inpatient visits may have increased because of respiratory disease worsening with exposure.

However, 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 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 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.

Last, 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

This study evaluated the relationship between short-term exposure to wildfire $PM_{2.5}$ and residential proximity and residence in a disaster zone, as a proxy for a mixture of health-harming exposures such as community disruption, smoke exposure, and stress and outpatient, ED, and inpatient visits among DME users in Southern California. Observed associations pointed to disruption of daily lives among those more exposed to wildfire, with missed outpatient care visits. We observed an association between elevated wildfire $PM_{2.5}$ concentrations and decreased next-day rate followed by increased rate of all-cause outpatient visits over 4/5 subsequent days as well as reduced all-cause outpatient visits among those living in proximity to the Woolsey Fire. Wildfire $PM_{2.5}$ was not associated with ED or inpatient visits, but Woolsey Fire proximity was associated with increased inpatient cardiorespiratory visits. This study adds to a literature on the health of vulnerable populations exposed to wildfires, which becomes more critical as wildfires frequency and severity increases with climate change. Protecting vulnerable populations that may be

harmed by exposures which others can avoid or endure is essential. More work is needed to understand the timing of health risks for vulnerable populations affected by smoke, fire, and evacuation.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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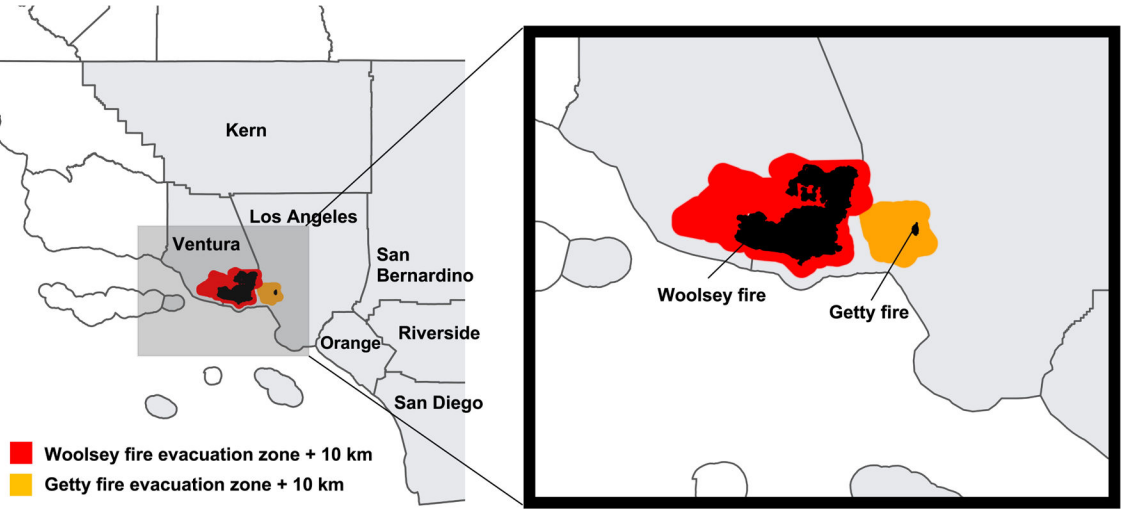

Figure 1:
Map of Southern California study area, shaded in grey, with counties labelled in black. Woolsey and Getty fire burn areas are shaded in black.

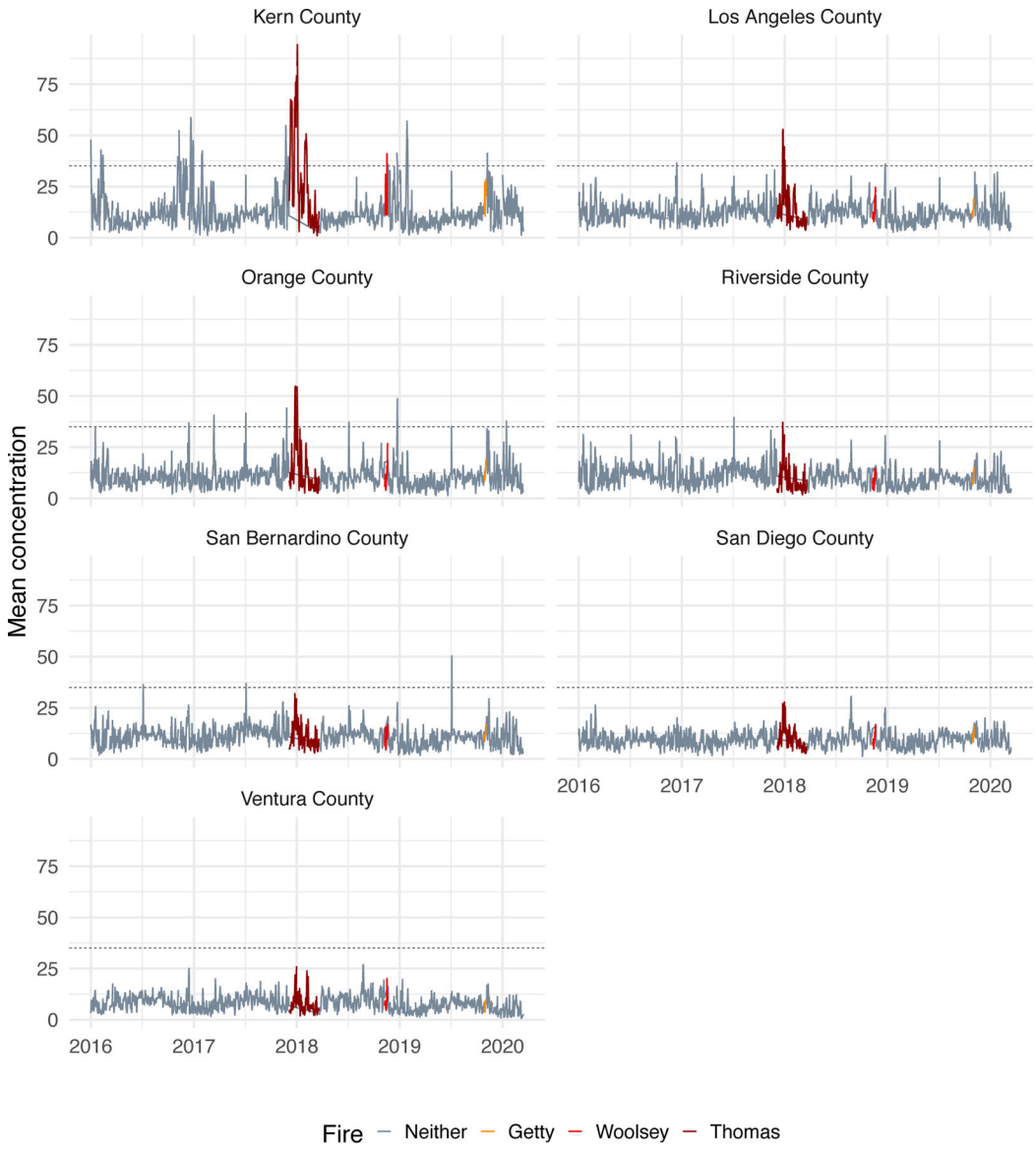

Figure 2:

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 US Environmental Protection Agency 35 $\mu g/m^3$ standard. Colored time periods represent measurements made while a wildfire was burning.

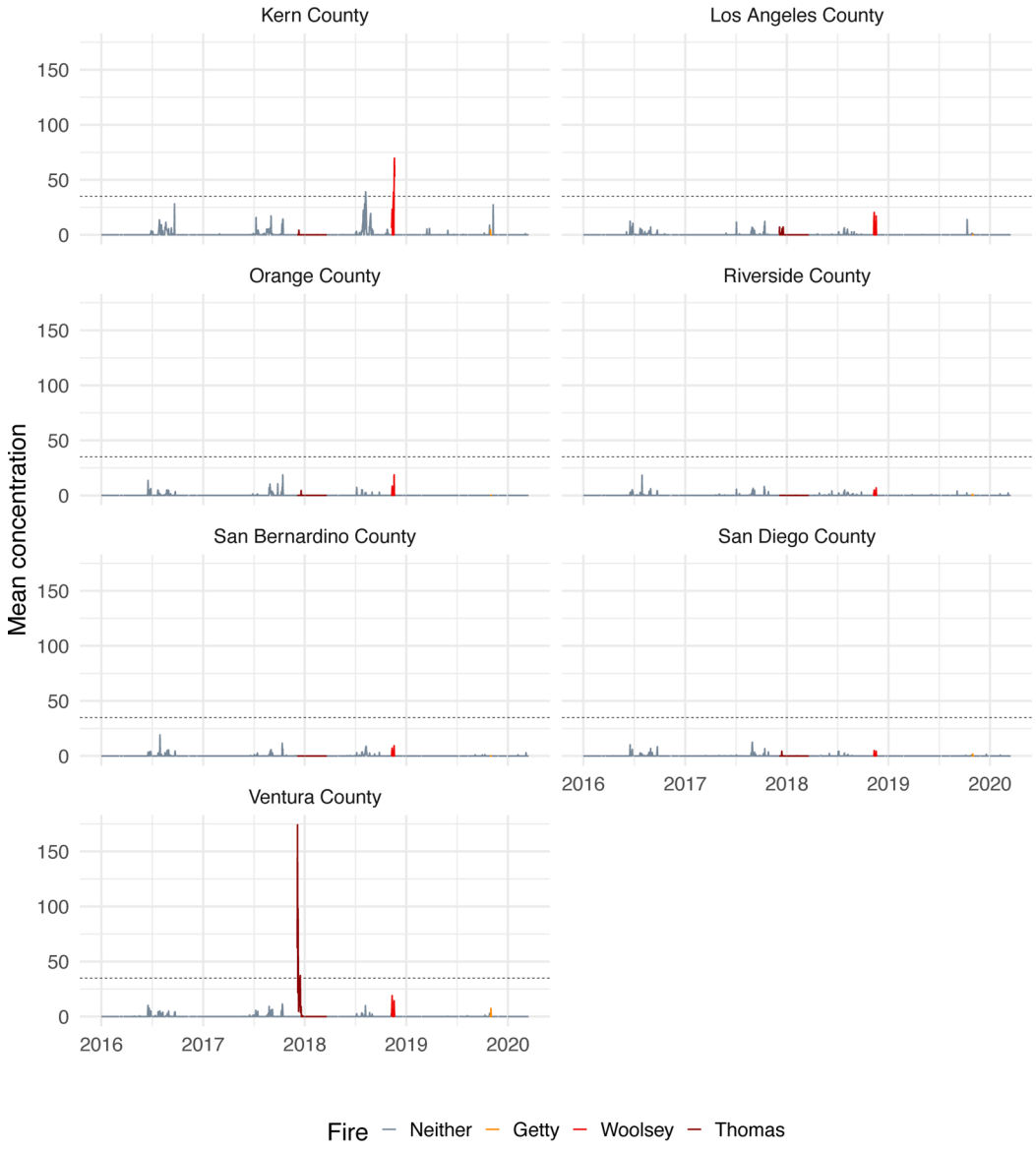

Figure 3:

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 US Environmental Protection Agency 35 $\mu g/m^3$ standard. Colored time periods represent measurements made while a wildfire was burning.

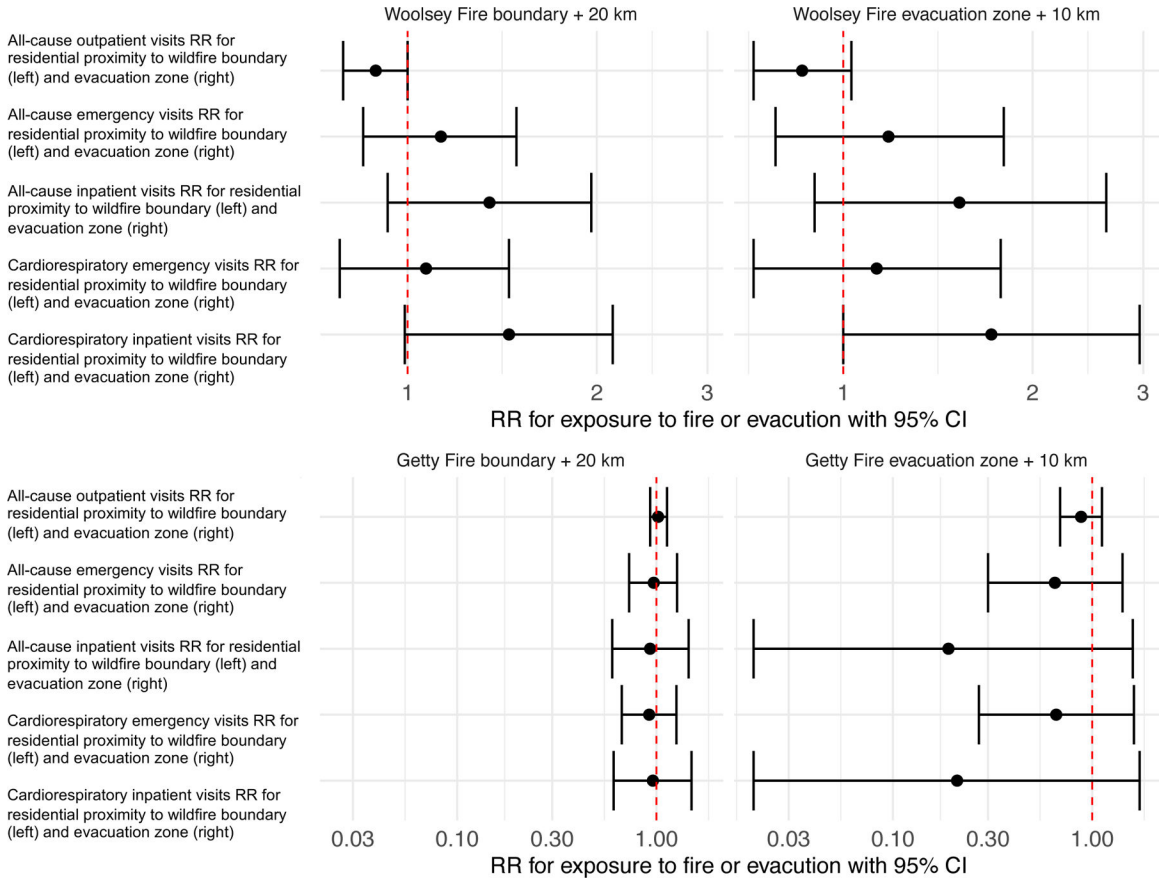

Figure 4:

Plots of rate ratios and 95% confidence intervals from a negative binomial model assessing the association between residential proximity to wildfires and evacuation zones PM and healthcare utilization among KPSC DME users.

We used negative binomial regression to evaluate the effect of wildfire evacuation or proximity during an active fire. The difference-in-differences estimators subtracted the change in visit frequency when the Woolsey or Getty Fire was burning versus not burning among control ZCTAs (difference 1) from the change in visit frequency when the Woolsey or Getty 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 $PM_{2.5}$, and added an offset for the size of the exposed population. DME, electricity-dependent durable medical equipment; KPSC, Kaiser Permanente Southern California; RR, rate ratio; ZCTA, Zip Code Tabulation Area.

Table 1:

Rate 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.

	Rate 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 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]
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]
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]
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]

[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). DME, electricity-dependent durable medical equipment; KPSC, Kaiser Permanente Southern California; ZCTA, Zip Code Tabulation Area.

Table 2:

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

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

[a]Negative binomial models included fixed effects for weekly mean wildfire $PM_{2.5}$ lags 0–2 weeks, 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). CI, confidence interval; ED, emergency department; ZCTA, Zip Code Tabulation Area.