Title
Wildfire, evacuation, and cardiovascular events: A spatial exposure approach

Authors
Arabadjis, Sophia D
Sweeney, Stuart H
Kenner, Catelynn E
et al.

Publication Date
2023-10-01

DOI
10.1016/j.apgeog.2023.103033

Wildfire, Evacuation, and Cardiovascular Events: A Spatial Exposure Approach

Sophia D Arabadjis[1], Stuart H Sweeney[1], Catelynn E Kenner[2], and Dominic J Tedesco[3]

[1]*Department of Geography*
University of California Santa Barbara
Santa Barbara, CA 93106-2150

[2]*Cottage Health Research Institute*
Santa Barbara, CA 93102

[3]*Department of Cardiothoracic Surgery*
Cottage Health
Santa Barbara, CA 93106

—

March 28, 2025

Funding Sources: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Declaration of Interests: None.

Abstract

Increasingly, adverse health effects from wildfire exposure are not limited to select populations in the wildland-urban interface. As wildfires continue to grow in frequency and intensity, they are also continuing to encroach on urban areas, putting larger and larger populations at risk. In this study we develop an innovative research design in the wildfire and health literature, and report results for a small scale implementation on California's central coast. Instead of focusing on smoke exposure and PM 2.5 or PM 10 as the primary physiological pathway linking wildfire and adverse cardiovascular health outcomes, we draw on a stress pathway as a potential link between stress and heart health. We use a novel spatiotemporal definition of wildfire exposure that is directly measurable at the individual level and acutely stressful: evacuation orders. Combining longitudinal health data from the dominant local hospital system in southern Santa Barbara County, California, we directly determine exposure to an evacuation order and smoke plumes from three large fires in the 2017 - 2019 wildfire period. Controlling for additional known risk factors, such as diabetes status and smoking status, we model the risk of secondary cardiovascular events (CVE) for 2,411 patients with existing cardiovascular disease. Roughly 16.2% of patients (n = 391) were exposed to an evacuation order. We found evacuation order exposure was not significantly associated with an increased risk of cardiac events for the CVD population, but estimates hovered between 12.5-16.3% over un-evacuated cohorts. Smoke exposures were not significantly associated with CVE risk in models adjusted for evacuation orders nor unadjusted models, and estimates of effects varied widely. Both the method and the findings have implications for public health departments, clinicians and wildfire researchers.

keywords: wildfire, survival analysis, spatial data, heart disease, evacuation

1 Introduction

Increasingly, adverse health effects from wildfire exposure are not limited to select populations in the wildland-urban interface. As wildfires continue to grow in frequency and intensity, they are also encroaching on urban areas, putting larger and larger populations at-risk. Adverse health outcomes associated with wildfires include various end points such as increased rates of hospitalizations, emergency department visits, and deaths (Reid et al., 2016a, Chang et al., 2022, Cohen et al., 2022, Heaney et al., 2022, Johnston et al., 2014), as well as exacerbation of specific illnesses such as respiratory illnesses (like asthma) (Heaney et al., 2022, Johnston et al., 2014, Brook et al., 2010, Chang et al., 2022, Mott et al., 2005), cardiorespiratory-related illnesses (like congestive heart failure) (Mott et al., 2005, Delfino et al., 2009, Reid et al., 2016a), and cardiovascular diseases/events (like stroke) (Heaney et al., 2022, Henderson Sarah B. et al., 2011, Moore et al., 2006, Johnston et al., 2014, Wen et al., 2022, Wettstein et al., 2018).

While research linking wildfire to health outcomes has blossomed across multiple fields in recent years, findings related to cardiovascular disease (CVD) and cardiovascular events (CVE) remain mixed (Wellenius et al., 2005, Delfino et al., 2009, Reid et al., 2016a, Wettstein et al., 2018, Heaney et al., 2022, Reid et al., 2016b, Moore et al., 2006). This inconsistency could be due to several common conceptual and methodological constraints in the CVE-wildfire literature. Conceptually, much of the current literature focuses on smoke or particulate matter as the primary pathway linking wildfire and adverse health outcomes (Reid et al., 2019, 2016a). From other disaster literature, there is evidence to suggest that earthquakes (Chan et al., 2013, Bazoukis et al., 2018), tsunamis (Nakagawa et al., 2009, Nakamura et al., 2013), hurricanes (Swerdel et al., 2014, Peters et al., 2014), and flood events (Ryan et al., 2015) may be associated with higher risk of cardiovascular events. This mechanism may manifest over longer periods than are typically studied in the smoke-exposure-motivated approaches (Nakagawa et al., 2009, Nakamura et al., 2013, Swerdel et al., 2014, Jordan et al., 2013, Leor and Kloner, 1996, Peters et al., 2014). Additionally, conceptualization and measurement of "exposure" to a wildfire varies widely across the literature, from purely temporal comparisons of "pre-fire" periods to "post fire" periods (Cohen et al., 2022, Moore et al., 2006), to a more nuanced spatial and temporal assignment of all persons in a statistical area, zip code or grid cell to an observed particulate matter concentration for a given time period (Delfino et al., 2009, Wettstein et al., 2018, Johnston et al., 2011, Thelen et al., 2013, Aguilera et al., 2020, Reid et al., 2019). These approaches introduce an assumption of homogeneity of exposure at the scale of analysis.

From a methodological viewpoint, most studies are also limited by indirect methods of individual exposure and rely on counts of new hospitalizations or emergency department visits in the aggregate. Within such counts, it is often not possible to disentangle those who were actually exposed (for example, to a wildfire plume), from those who were not. Additionally, these aggregate measures, as opposed to individual measures, cannot account for compositional shifts of patient case-counts before and after events (such as changing mixes of socio-demographic characteristics of the patient case-counts in the immediate aftermath of an exposure event), and may dilute the size of the response given the stimulus (Heaney et al., 2022, Reid et al., 2016b, Mott et al., 2005). Finally, some studies attempt to normalize rates (of hospital admissions or emergency department visits) against an at-risk population estimate for a specific areal unit (Wettstein et al., 2018). This approach introduces additional variability into the denominator of these rates and it is not clear how such variation may propagate into estimates of effects and standard errors.

In this study we pursue an alternative approach that addresses some of these constraints and offers an innovative study design in the wildfire and health literature. Instead of focusing on smoke exposure and PM 2.5 or PM 10 as the primary physiological pathway linking wildfire and adverse cardiovascular health outcomes, we draw on a stress pathway as a potential link between stress and heart health. Though the biological mechanisms are not well understood, there is evidence to suggest one such mechanism may be neurocardiogenic, linking acute emotional or physical stress states to stress cardiomyopathy and/or myocardial infarction (heart attack) (Hollenberg, 2016, Boland et al., 2015, Chan et al., 2013, Swerdel et al., 2014, Peters et al., 2014).

Taking this pathway as our baseline, we use a novel spatiotemporal definition of wildfire exposure that is directly measurable at the individual level and acutely stressful: evacuation orders. Combining longitudinal health data from the dominant local hospital system in southern Santa Barbara County, California, we directly determine exposure to an evacuation order and smoke plumes from three large fires in the 2017 - 2019 wildfire period. Controlling for additional known risk factors, such as diabetes status and smoking status, we model the risk of secondary cardiovascular events (CVE) for patients with existing cardiovascular disease[1] after exposure to evacuation orders and smoke plumes. With an individual-level approach, we can provide new insights into compositional shifts and disease exacerbation after exposure. Additionally, because we focus on those with existing cardiovascular disease, we are able to both narrow our at-risk pool for a cleaner interpretation of any uncertainty, but also contribute existing research on CVE risk for a large[2] CDC-classified vulnerable population (Tsao et al., 2023).

2 Methods and Materials

This study has been approved by the Santa Barbara Cottage Hospital Institutional Review Board.

2.1 Evacuation Order Data

From October 2016 through the end of May 2019, there were a total of 24 named[3] fires that burned in Santa Barbara County (see Figure 1). Three of these fires necessitated evacuation

[1]Cardiovascular disease diagnoses include Chronic Heart Disease, Heart Failure, stroke, and hypertension per the American Heart Association.

[2]Approximately 127.9 million Americans, or 48.6% of the population aged 20 years or older, have at least one cardiovascular disease diagnosis (Tsao et al., 2023).

[3]Fires that burn more than 300 acres receive a reference name from one of CAL FIRE, USDA Forest Service Region 5, USDI Bureau of Land Management, National Park Service and/or local agencies (CAL FIRE, 2022).

orders: the Alamo, Whittier, and Thomas fires. Due to local topographic features, vegetation and wind patterns, wildfires on the Central Coast can move at very high speeds and quickly consume structures. In this area, evacuations for wildfire are often sudden, unpredictable, and urgent. For example, the Thomas Fire was the largest and fastest moving of the fires that burned into Santa Barbara County during the study period. While it burned roughly 281,000 acres in total; 100,000 acres burned in the first 48 hours (CAL FIRE, 2022). The final fire perimeters are mapped in Figure 1.

Evacuation orders issued in response to the Alamo, Whittier and Thomas fires were collected from the County of Santa Barbara Evacuation Press Releases, official Twitter handles, and personal correspondence with local departments (DePinto, 2017). For each press release, written descriptions of street names and locations were digitized using QGIS version 3.16 (QGIS Development Team, 2009) to derive spatial extent. To the extent that evacuation orders were repeated across press releases and days, evacuation zones were re-encoded as a new polygon with a new date attribute to generate the daily evacuation order data set. Otherwise, duration of evacuation orders were not recorded.[4] Patients were considered exposed if their electronic medical record derived date-referenced residential location(s) coincided with any of the date-referenced evacuation zones. That is, patients were only exposed if their current address location at the time of the evacuation order fell within an evacuation zone polygon. Due to small sample sizes, mandatory versus voluntary orders were not distinguished, and the time-to-exposure was limited to the time of the first evacuation order for each patient.

[4]We were unable to assess the duration of the evacuation orders because of data limitations. When residents were allowed back into the evacuated zones was not as clearly documented as the initial evacuation. Hence, our results are limited in their interpretation to those having experienced any evacuation order as opposed to being able to assess the effects of the duration of those orders. However, given the literature on CVE and other natural disaster, we are unsure that assessing the end of an evacuation order has a meaningful interpretation – it does not necessarily align with the end of a stress response.

2.2 Electronic Medical Record Data

In partnership with the predominant local hospital system, we obtained electronic medical records for all qualifying cardiovascular event-related (CVE-related) patient visits between October 1, 2016 and June 1, 2019. Qualifying CVE diagnoses were selected as diagnoses likely to be exacerbated by increased stress per our physician partner and based on the International Classification of Diseases Tenth Revision (ICD-10) system (see Table 1). Qualifying ICD-10 codes were selected by our physician author and included all child codes within the following: I10, I11, I13, I15, I20-I25, I40, I42-I52, I71, R00, R07.1, R07.2, R07.8, R07.9, and R94.3. These codes encompass a range of cardiac dysfunctions including severe diagnoses (stroke, cardiac arrest, acute myocardial infarction) and potentially less severe diagnoses (hypertensive heart disease and chest pain). Included diagnosis codes generally align well with other studies using similar methods (Reid et al., 2016a, Wellenius et al., 2005, Delfino et al., 2009, Heaney et al., 2022, Cohen et al., 2022, Reid et al., 2016b, Henderson Sarah B. et al., 2011, Chan et al., 2013, Swerdel et al., 2014, Lim et al., 2012, Yang et al., 2017, Wen et al., 2022), and include common cardiovascular disease (CVD) as well as symptomatic diagnoses (e.g. R07.9, "chest pain, unspecified") to better capture a range of potential exposure effects. For the duration of the paper, we refer to the "qualifying cardiac event" as this initial CVE-related visit for each patient.

The data include 7,364 patient visits across 5,318 unique patients distributed over the period. Though we initially requested dates of first qualifying CVD diagnosis for each patient, due to an electronic medical record (EMR) system migration in the fall of 2016, retrospective diagnosis dates were not available. Additionally, because our methods rely on accurate time of both study entry (in this case initial CVD diagnosis date) and secondary CVE (if observed), we limited our data to patients whose first CVE diagnosis in the EMR coincided with their first visit in the EMR (n=3,867) This restriction is an assurance of accuracy and data validity and is akin to imposing a sampling window on our study design. For the 3,867 patients there were 7,088 unique (and dated) associated addresses that overlapped the study period. We removed addresses indicating homelessness or shelter housing, post office boxes, listings of "No Address on File" and like statements (n=401). Using Santa Barbara County Assessor parcel data from 2016, we matched[5] addresses in an iterative fashion and extracted point centroids of each polygonal parcel. We excluded addresses with no plausible match or those outside of Santa Barbara County (n=933). Of the eligible addresses, we achieved a 90.3% match rate, or 5140 of 5693.

Additionally, because of the decentralized and fragmented nature of healthcare provision in the United States, some patients may receive regular cardiovascular care from providers outside the hospital system, but use the study hospital system locations for extreme cases or emergencies. Such cases threaten the integrity of the research inference (interpreting secondary CVE risk requires both onset and sequential event) as well as the effect size of estimates (timing between visits could be artificially inflated as patients may receive care for another CVE from a different system). In an attempt to control for these difficulties in administrative data, we defined a geographic boundary for the study area that captures commuting flows and the hospital catchment and is informed by the Regional Wildfire Mitigation Project (extended RWMP) for the area (Wesolowski, 2021); we assume that residents of this area are likely to travel to the study hospital system locations for cardiovascular care (see Figure 1).[6] To be included in the final patient sample, we required individuals to have at least one valid (matched) address within the extended RWMP over the time period. The final sample size was 2,411 patients, aged 18-87 years.

Using the same set of diagnosis codes, we restricted secondary CVEs to those that occurred through an emergency department so as not to accidentally catch scheduled follow-up care visits. Though conservative, this estimation method for secondary visits provides a cleaner interpretation of events, and we can assume independent events for each visit. In addition to date of hospital visit and dated address histories, the EMR records include

[5] The exact address matching schema is available on request.

[6] We conducted a sensitivity analysis using other areal units (full county, patient zip code, and census tracts) to better parse the the effects of the distance decay on the model estimates. Our results suggested that the extended RWMP aligns best with our true hospital catchment area.

patient sex, date-of-birth, preferred language, insurance status, smoking history, history of heart surgery, diabetes status and diagnosis. Diabetes status, smoking status, age and sex are all associated with onset of CVD (Benjamin et al., 2019). Initially, investigators were concerned that preferred language could be associated with stress levels hence its inclusion in the final models. EMRs often do not provide a direct indicator of socio-economic status; we used insurance type as an imperfect proxy. These variables are summarized in Table 2.

2.3 Smoke Exposure Data

Smoke data was collected from October 1st, 2016 through May 31st, 2019 from the National Oceanic and Atmospheric Administration (NOAA) Office of Satellite and Product Operations (OSPO) Hazards Mapping System (HMS) Fire and Smoke Product (NOAA OSPO HMS, 2018). Implemented in 2003, HMS relies on polar and geostationary satellite observations and expert image analysts who digitize the smoke plumes. Smoke plumes are further categorized based on density of the plume (thin, medium, thick). Though the HMS data do not directly measure particulate matter, they remain a common choice in the literature (Wettstein et al., 2018, Henderson Sarah B. et al., 2011). The HMS data set contains several readings per day (sometimes from different satellites). In processing the data, we chose to create daily unions of smoke extents to capture the broadest spatial extents by density type. On some days the extents of the polygons overlapped (that is a "medium" plume may have been contained within a larger "thin" density plume), but other days some areas were exposed to one density type (e.g. "medium") without being exposed to "thin". In light of this phenomena, we also created an "any" density plume each day to capture exposure to any density of plume. In each case (thin, medium, thick or any), patients were considered to have been exposed to a day of smoke if their date-referenced residential location was contained within a date-referenced smoke plume polygon.

2.4 Statistical Analysis

The extended Cox Proportional Hazard Model (Cox PH) is an attractive method for analyzing time-structured exposures and outcomes for its ease of use and interpretation. In our case we may think of each individual having a set or triple $[T_i, \delta_i, [\mathbf{x}_i(t), 0 \leq t \leq T_i]]$, where $i = 1, ..., n$ indexes the patients in the study, T_i is the time to the secondary CVE or end of study, δ_i indicates event status (1 if CVE observed or 0 if censored), and $\mathbf{x}_i(t) = [x_{i1}, x_{i2}, ..., x_{ip}]$ the vector of p covariate values at time t. Following the work of Klein and Moeschberger as well as Aalen, Gjessing, and Håkon (Klein and Moeschberger, 2010, Aalen et al., 2008), the extended cox model hazard can be written:

$$h(t|x_{i1}, x_{i2}, ..., x_{ip} = \mathbf{x_i}) = h_0(t)e^{\boldsymbol{\beta}^T \mathbf{x_i}(t)} = h_0(t) \exp\Big\{\sum_{k=1}^{p} \beta_k x_{ik}(t)\Big\}$$

where $h_0(t)$ is the baseline hazard rate which remains unspecified, and $\boldsymbol{\beta} = (\beta_1, ...\beta_p)^T$ is the vector of regression coefficients that describe the effects of the covariates at time t. The $x_{ik}(t)$ terms may be time-dependent covariates (such as exposure to an evacuation order or smoke plume), or may be constant over the time period (such as sex or diabetic status) for the i^{th} individual. The extended Cox model assumes that the hazards between individuals of opposing covariate groups are proportional.

In this analysis, we made explicit choices about how to code the evacuation exposure and smoke plume exposure variables. The evacuation order exposure is coded as a binary variable. For any given patient, $evac_{it} = 0$ if $t < T_{\text{exposure}}$, for $t \geq T_{\text{exposure}},\ evac_{it} = 1$; where T_{exposure} is the time from study entry to evacuation exposure. Similarly, we coded exposure to a smoke plume (of any density) as binary variables at several cumulative time points where $j = 1$ day, 3 days, 7 days, or 10 days of total exposure to a plume type. For any given patient, $smoke_{jit} = 0$ if $t < T_{\text{exposure},j}$ for $t \geq T_{\text{exposure},j},\ smoke_{jit} = 1$; where $T_{\text{exposure},j}$ is the time from study entry to the j^{th} day of cumulative smoke exposure of a specified type (thin, medium, thick, or any). Ultimately, we present results from five separate models each with a different smoke exposure specification.[7] Model 1 is not adjusted for any smoke exposure and only tests effects of evacuation orders and covariates on secondary CVE risk. Models 2-5 adjust for exposure to 1-day cumulative "thin", "medium", "thick", or "any" smoke exposure from the smoke polygon data as well as all covariates and evacuation orders.

As is recommended practice for studies with multiple events per subject or more than one event type (Terry M. Therneau and Patricia M. Grambsch, 2000, Therneau, 2021) we used robust standard errors in this analysis. We used traditional selection criteria (AIC, BIC, Cox weighted residual tests for proportional hazards) for model specification, selection and fit. We consider $\alpha = 0.1$ for Type I error control because of the exploratory nature of this study design.

In our consideration of uncertainty, we use the evacuation order parameter estimates from each model specficiation (none, thin, medium, thick, any smoke exposure) and the associated standard errors as inputs into a lognormal distribution[8] for which we simulated values along a continuum. This is consistent with the parametric assumptions of the model. We generated both cumulative density functions and probability density functions for each estimate.

All analyses were completed in R version 4.1.3 (R Core Team, 2022).

3 Results

Within the study period, 2,411 patients had a qualifying cardiovascular event. Of these patients, 425 developed a secondary event during the study period (17.6%). There were 146 total deaths (not all due to CVE), 12 of which were deaths on arrival. All deaths not due to CVE were treated as censored in our data. While deaths clustered at the end of every calendar year, there was no observed difference in the mean arrival rate of deaths between December 1, 2017-January 15, 2018 (Thomas Fire period) and the year prior. However, in the

[7] We also include similar model results with smoke covariates but unadjusted for evacuation orders in the supplementary material.

[8] The lognormal transposed the estimates on the link scale to the odd-ratio scale for easier interpretation.

year following the mean rate of arrival was significantly lower ($t_{df=58} = -2.3291, p < 0.05$). Of the 2,411 patients, a total of 391 went on to experience an evacuation order of any type: 109 patients experienced a mandatory evacuation order due to an encroaching wildfire, 368 patients experienced a voluntary order, and 86 would have experienced both (transition in either direction). Because of small sample sizes, we chose not to pursue an analysis based on the type of evacuation order exposure. Of the evacuation exposed cohort, 55 developed a secondary CVE. The remaining 370 secondary events were observed in the unexposed cohort. The median wait time until evacuation exposure was 213 days for patients who were eventually evacuated. For patients who had an observed secondary CVE, the wait time ranged from 1 to 438 days following the initial event and study entry.

Trends in diagnosis and visits around the fire periods are reported in detail in the supplementary materials, but the evidence did not suggest a compositional shift (such as an increase in visits by those with existing cardiovascular disease in the immediate wake of evacuation exposure). There was a slight increase in diagnoses and visits during the active evacuation order period around the Thomas fire, but not for the Alamo or Whittier fires (which had concurrent evacuation orders). As compared to other years, the mean arrival rate during the 6-week Thomas Fire period was not significantly different from the year prior (mean rate of 3.1 per day), but was significantly more than the year post (2.1 per day, two-sided t-test $p < 0.05$). The most frequent diagnosis code was atrial fibrillation and flutter (33.4% of patients presenting), followed by heart failure (21.1%) and chest pain (17.9%). Note that many of these diagnoses codes occurred in conjunction with other related (or unrelated) codes. The most common diagnosis codes for secondary cardiovascular events were heart failure (44.7% of patients), atrial fibrillation and flutter (41.9%), followed by chronic ischemic heart disease (19.1%).

3.1 *Extended Cox Proportional Hazard Model Results*

In the literature, it is common to test multiple day lags to assess the effects of wildfire smoke exposure on hospital visits and/or admissions. While different researchers find different results, several authors have suggested that 1-day lags are associated with an increase in CVD-related visits and/or admissions (Wellenius et al., 2005, Heaney et al., 2022, Wettstein et al., 2018). Hence, to keep our results aligned with these findings, we included a one-day cumulative smoke exposure variable (thin, medium, thick, or any) in our final model selections.[9] After assessing model fit and diagnostics, we present five different specifications based on the differing smoke plume densities (none, thin, medium, thick, and any). Note that the time within the study each individual crossed the threshold of three days of plume exposure depends on the spatial extent of each plume type. Additionally, the exact timing of the exposure for each individual is not constant across plume types.

The parameter estimates are presented with respect to reference groups for each variable: English-speaking, female, under 60 years of age, commercial insurance and no history of heart surgery, diabetes, or smoking, and no smoke plume exposure or evacuation exposure. The parameter estimates are interpreted as an increase in the hazard of secondary CVE with respect to the reference group. The parameter estimates from these models are located in Table 3, and are visually represented in Figure 2. With no smoke indicator included in the model, we see a non-significant but positive effect of evacuation exposure on risk of secondary CVE (0.124, 90%CI [-0.127,0.376]), which indicates a 13.2% increase in risk as compared to the unevacuated group ($100 \cdot (e^{0.124} - 1)$). The increased risk effect stays positive and relatively consistent across different smoke specifications, with increases in risk ranging from 12.5-16.3% as compared to unexposed cohorts after controlling for all other covariates.

While the 90% confidence intervals contain zero, in an exploratory context it is useful to further examine the uncertainty. Embedded in our study design, we have a strong prior that

[9] Estimates from both three-day cumulative smoke exposure model fits and model fits with only smoke exposures (no evacuation) are available from the authors.

evacuation orders can only increase CVE risk or not change the risk at all; evacuation orders cannot be protective (or lower risk). Hence, we might consider the estimated parameter distribution at or above an actionable increment. We consider a 10% increase in risk as a clinical benchmark and threshold at which a clinician or emergency service provider may consider the risk to be actionable. Figure 3 displays the cumulative distribution functions and densities for the evacuation order effects under each smoke regime (none, any, thick, medium or thin.) From the cumulative distributions (Figure 3 (a)), a 10% increase lies between .36 and .44 probability depending on the smoke plume type specification, which suggests that in more that 50% of random draws, the effect of evacuation exposure on risk of secondary CVE for this population would be greater than a 10% increase. To summarize this visually, Figure 3 (b) shows the density functions for each parameter estimate with the dotted line indicating the 10% increase in risk. In each case, more than 50% of the parameter's distribution lies to the right of the line.

Other expected covariate relationships hold. As age increases, the risk of secondary cardiac event also increases. A concurrent diagnosis of diabetes mellitus is associated with increased risk, as is smoking status and, to a lesser extent, history of heart surgery. There is no apparent difference in risk by sex. There are significant increases in risk by insurance type (though these distinctions are likely due to both coinciding changes in age and insurance as well as unmeasurable differences in SES seeping through insurance type). Finally, during the evacuation periods, particularly for the Thomas Fire period, there was some concern that evacuation orders were not reaching Spanish-speaking populations, potentially contributing to the stress of the period. However, preferred language did not appear to be related to CVE risk.

To further understand the role of smoke in this model framework, we also ran models with one-day cumulative smoke exposures and covariates without adjusting for evacuation order exposure. These models generated very similar estimates of coefficient and standard errors for all covariates (all estimates were within a tenth of evacuation-adjusted model estimates, see supplementary materials for details). Given this, the 1-day cumulative smoke measures do not appear to be associated with CVE risk, adjusted for evacuation order or otherwise. While simpler models with evacuation order and cumulative smoke measures showed some consistent directions of association across densities and exposure cutoffs, the adjusted models do not. Estimates for smoke effects range in both magnitude and direction, and, with the exception of the thin plume exposure, the standard errors are an order of magnitude larger than the effect sizes.

4 Discussion

In this study we had two aims: the first was to provide a proof-of-concept for an innovative study design to assess health risks related to wildfire exposure, and the second was to implement the method in a small setting to assess the effects of wildfire evacuations and smoke exposure on the risk of a secondary cardiovascular event for patients with existing cardiovascular disease. In pursuit of these aims, we've carefully described the logic, data sources and variable construction necessary to conduct such a study, and operationalized the design within the Santa Barbara County context. We collected electronic medical record data for CVE-related visits from October 1, 2016 through June 1, 2019, and combined patient addresses with county parcel extents, daily smoke extents, and evacuation order extents for three fires that occurred within the time period. We then modeled the effects of these constructed variables on cardiovascular event risk while controlling for known covariates.

Within the broader context of wildfire smoke exposure and CVEs, evidence of an effect is mixed. Some studies have found slight increases in number of admissions or emergency department visits for stroke, cerebrovascular disease and congestive heart failure (Wellenius et al., 2005, Delfino et al., 2009, Reid et al., 2016a, Wettstein et al., 2018), where others have found null results (Heaney et al., 2022, Reid et al., 2016b, Moore et al., 2006, Reid et al., 2016a). Our study contributes to this open question; even for a CDC classified vulnerable population (those with existing CVD), we find no evidence of a consistent association between

1-day smoke plume exposure and CVE risk. Given the open question in the literature about the effects of smoke on CVD outcomes, had smoke been strongly associated with adverse CVD outcomes, we would have expected consistent large positive estimates that generally increased with both density of plume as well as days of exposure (j). After fitting our models, the effects of smoke plume effects on risk of secondary CVE are inconsistent and noisy. This could be due to our choice of the HMS smoke exposure variable, which as Feduda et al. (2020) note, may not capture peak PM 2.5 exposures on the ground and offer no information with regards to night-time plumes (Fadadu et al., 2020).

Alternatively, the inconsistency and noise could also be due to heterogeneity of experience of individuals. There is a lack of quantification of avoidance behaviors for mitigating exposure to poor air quality or smokey days in this context. While short-term woodfire smoke has been shown to be detrimental in controlled environments (Brook et al., 2010), in natural settings, air quality warnings, visible smoke, and adherence to risk-reduction strategies (such as limiting outdoor time, masking, air filtration, relocation) may all mitigate the risk of particulate matter exposure from wildfire smoke.

In the actual assessment of evacuation order effects, our data and modeling are, at best, suggestive. The point estimates of the evacuation order effects range from 12-16% over the unexposed population depending on the smoke specification, after controlling for known CVE risk factors. While the point estimates may be above an actionable threshold for clinicians, our estimates lack precision and are not statistically different from zero. In our consideration of the sources of uncertainty, we can point to two mechanical issues at play. First is the small sample sizes, particularly for the exposed population. Of our 2,411 patients, only 391 were exposed to an evacuation order and of those only 55 experienced a second cardiovascular event. These sample size constraints decrease the likelihood of recovering a strong signal, and made testing important interactions (such as advanced age and evacuation order exposure) impossible. As wildfires continue to grow in scope and scale and data sharing practices improve, larger studies that make use of this method may be able to more precisely estimate effects.

Secondly, though the evacuation orders provide a direct measure of exposure, the stress exposure itself may be experienced heterogeneously within the exposed group. Other factors, such as distance to the active fire line, number of dependents in the household, presence of pets or livestock, duration of exposure, availability of social capital, socio-economic status and resources, and media hype within the period could all contribute to an individual's stress response.[10] Additionally, while we were unable to distinguish between mandatory and voluntary evacuation orders, patterns of evacuations (immediate mandatory evacuation, versus voluntary then mandatory) may engender different responses. Our concern here aligns obliquely with a mature body of literature in health geography arguing for more attention to correctly measuring an individual's exposure to environmental risks by carefully defining spatial and temporal dimension of that risk (Spielman and Yoo, 2009). While that literature specifically addresses improved estimation of neighborhood effects – mostly exposure to chronic stressors – our work makes a similar case for acute environmental stressors. It is unclear how to resolve the heterogeneous exposure or experience of stress within evacuation zones short of prospective studies with wearable heart rate sensors or direct measures of cortisol. Such studies could also incorporate mandatory versus voluntary evacuation order exposure, track duration of evacuation exposures, and incorporate better measures of individual socio-economic status, social capital, and available resources.

Still, we believe that exposure to evacuation orders and the stress pathway provide a more precise indicator and mechanism than smoke exposure for assessing wildfire effects on cardiovascular risk. Because it is difficult to measure at the individual level, smoke exposure tends to be interpolated or estimated across wide expanses (Reid et al., 2016a, Henderson

[10] Additionally, socio-economic status is also intrinsically linked with CVD risk through proximal pathways like diet, exercise, occupation, agency and others. SES is a structural determinant of (heart) health (World Health Organization, 2010). This study was constrained in its ability to assess those pathways; the best we could do was to use insurance category. As our reviewer suggests, this is a far from perfect proxy, and SES, social-capital, and individual resources impact both risk of initial CVD, disease progression/control, and stress response to evacuation exposure. Future research should aim to more explicitly assess these pathways and disentangle SES-effects on the stress pathway of secondary CVE.

Sarah B. et al., 2011, Delfino et al., 2009). While newer machine learning approaches for smoke dispersion combine chemical transport models and multiple inputs from monitors, land use regression models, and satellites (Humphrey et al., 2019, Reid et al., 2015, Reid and Maestas, 2019), all exposures are still estimates that may be systematically biased when combined with individual data. Specifically in terms of cardiovascular event risk, recent research has pointed to overestimation of the association between urban PM 2.5 exposure and CVD, largely due to mismatches in scale and aggregation (Modifiable Areal Unit Problem and Uncertain Geographic Context Problem) (Humphrey et al., 2019). In contrast, in our approach evacuation order boundaries function as another type of exposure; an exposure that is both precise (not imputed from sensors) and carries substantial consequences including potential loss of property and life.

A final strength of this study is the population at-risk. Our focus on patients with existing disease was intentional from both a health and statistical standpoint. From the health perspective, Nearly 49% of the population of Americans aged 20 years or older have at least one CVD diagnosis, and CVD remains a leading cause of death in the United States (Tsao et al., 2023). Existing research on prevention of secondary CVE suggests that the existing CVD population has a CVE risk 20-30% higher than baseline risk within a five-year period (Kaasenbrood et al., 2016, Kerr et al., 2009). As wildfires and natural hazards increase in strength and frequency, so too will evacuation order exposures, and the risk posed by stress responses will not be evenly distributed across the exposed population.

Some studies use census tract or census block population estimates to identify the exposed population in the definition of rates (Wettstein et al., 2018). This is particularly problematic given the sampling variation in American Community Survey estimates at the tract and block group level, which is further accentuated when rates need to be disaggregated (by age group, race/ethnicity, etc.) (Folch et al., 2016, Spielman et al., 2014). From a statistical standpoint, failing to account for this sampling variation leads to grossly overstated precision of the resulting estimates. While no retrospective method is perfect, our choice of population dramatically limits the variability within the at-risk population. With increasing data access, we hope more researchers will consider an approach like this one.

5 Conclusion

In this study we outlined an explicit spatial exposure approach to assess the relationship between cardiovascular events and wildfire using wildfire evacuation orders. We then demonstrated feasibility with a small sample from Southern Santa Barbara County. Though we do not have conclusive evidence suggesting a marked increase in CVE risk after exposure to an evacuation order, our methods has implications for public health officials, clinicians, and wildfire health researchers. For public health practitioners, this study design relies on accurate, shared electronic medical record data within a given area. Because of the fractured nature of the healthcare landscape in the United States, advocating for shared data structures is critical to make larger studies in this vein feasible. For clinicians, implications are two fold. First, clinical providers should likely be on alert for symptoms related to cardiac dysfunction when wildfires are active in their community of practice, especially for populations that may present with different symptoms, such as women and the elderly. Secondly, accurate data at the point of entry is extremely important for retrospective studies such as this, including accurate addresses. For wildfire health researchers, or other disaster health researchers, we have proposed a viable strategy to precisely measure effects of evacuation-stress-CVE pathway and with larger samples, the precision should improve. Our hope is that this method gets taken up more broadly, and inspires improved study designs in the field.

6 Acknowledgments

The authors would like to acknowledge the guidance and support of Mrs. Laura Isaacs and Dr. Peter G. Arabadjis, MD.

References

Odd O. Aalen, Ørnulf Borgan, and Håkon K. Gjessing. *Survival and event history analysis: a process point of view.* Statistics for biology and health. Springer, New York, 2008. ISBN 978-0-387-68560-1.

Rosana Aguilera, Kristen Hansen, Alexander Gershunov, Sindana D. Ilango, Paige Sheridan, and Tarik Benmarhnia. Respiratory hospitalizations and wildfire smoke: a spatiotemporal analysis of an extreme firestorm in San Diego County, California. *Environmental Epidemiology*, 4(5):e114, October 2020. ISSN 2474-7882. doi: 10.1097/EE9.0000000000000114. URL `https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7941788/`.

George Bazoukis, Gary Tse, Katerina K. Naka, Vasiliki Kalfakakou, Konstantinos Vlachos, Athanasios Saplaouras, Konstantinos P. Letsas, Panagiotis Korantzopoulos, Costas Thomopoulos, Paschalia Michelongona, Xenophon Bazoukis, Violeta González-Salvado, Tong Liu, Lampros K. Michalis, Adrian Baranchuk, Tomonori Itoh, Michael Efremidis, Costas Tsioufis, and Stavros Stavrakis. Impact of major earthquakes on the incidence of acute coronary syndromes - A systematic review of the literature. *Hellenic journal of cardiology: HJC = Hellenike kardiologike epitheorese*, 59(5):262–267, October 2018. ISSN 2241-5955. doi: 10.1016/j.hjc.2018.05.005.

Emilia J. Benjamin, Paul Munter, Alvaro Alonso, Marcio S. Bittencourt, Clifton Callaway, April P Carson, and Alanna M. Chamberlain. Heart Disease and Stroke Statistics—2019 Update: A Report From the American Heart Association. *Circulation*, 139:473, March 2019. doi: 10.1161/CIR.0000000000000659.

Torrey A. Boland, Vivien H. Lee, and Thomas P. Bleck. Stress-induced cardiomyopathy. *Critical Care Medicine*, 43(3):686–693, March 2015. ISSN 1530-0293. doi: 10.1097/CCM.0000000000000851.

Robert D. Brook, Sanjay Rajagopalan, C. Arden Pope, Jeffrey R. Brook, Aruni Bhatnagar, Ana V. Diez-Roux, Fernando Holguin, Yuling Hong, Russell V. Luepker, Murray A. Mittleman, Annette Peters, David Siscovick, Sidney C. Smith, Laurie Whitsel, and Joel D. Kaufman. Particulate Matter Air Pollution and Cardiovascular Disease. *Circulation*, 121(21):2331–2378, June 2010. doi: 10.1161/CIR.0b013e3181dbece1. URL `https://www.ahajournals.org/doi/10.1161/CIR.0b013e3181dbece1`. Publisher: American Heart Association.

CAL FIRE. CAL FIRE USDA Forest Service Region 5 USDI Bureau of Land Management National Park Service: Fire 1980 through 2019, March 2022. URL `https://services1.arcgis.com/4TXrdeWh0RyCqPgB/ArcGIS/rest/services/Fire`$_1980_{2019_{WFL1/Feature}}$

Christina Chan, John Elliott, Richard Troughton, Christopher Frampton, David Smyth, Ian Crozier, and Paul Bridgman. Acute myocardial infarction and stress cardiomyopathy following the Christchurch earthquakes. *PloS One*, 8(7):e68504, 2013. ISSN 1932-6203. doi: 10.1371/journal.pone.0068504.

Andrew Y. Chang, Annabel X. Tan, Kari C. Nadeau, and Michelle C. Odden. Aging Hearts in a Hotter, More Turbulent World: The Impacts of Climate Change on the Cardiovascular Health of Older Adults. *Current Cardiology Reports*, 24(6):749–760, June 2022. ISSN 1523-3782, 1534-3170. doi: 10.1007/s11886-022-01693-6. URL `https://link.springer.com/10.1007/s11886-022-01693-6`.

Odeya Cohen, Stav Shapira, and Eyal Furman. Long-Term Health Impacts of Wildfire Exposure: A Retrospective Study Exploring Hospitalization Dynamics Following the 2016 Wave of Fires in Israel. *International Journal of Environmental Research and Public Health*, 19(9):5012, April 2022. ISSN 1661-7827. doi: 10.3390/ijerph19095012. URL `https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9099700/`.

R. J. Delfino, S. Brummel, J. Wu, H. Stern, B. Ostro, M. Lipsett, A. Winer, D. H. Street, L. Zhang, T. Tjoa, and D. L. Gillen. The relationship of respiratory and cardiovascular hospital admissions to the southern California wildfires of 2003. *Occupational and Environmental Medicine*, 66(3):189–197, March 2009. ISSN 1351-0711, 1470-7926. doi: 10.1136/oem.2008.041376. URL `https://oem.bmj.com/content/66/3/189`.

Gina DePinto. County of Santa Barbara Evacuation Press Releases. Cumulative Press Releases, County of Santa Barbara Executive Office, Santa Barbara, December 2017. URL `https://www.countyofsb.org/2853/Press-Releases`.

Raj P. Fadadu, John R. Balmes, and Stephanie M. Holm. Differences in the Estimation of Wildfire-Associated Air Pollution by Satellite Mapping of Smoke Plumes and Ground-Level Monitoring. *International Journal of Environmental Research and Public Health*, 17(21):8164, November 2020. ISSN 1660-4601. doi: 10.3390/ijerph17218164.

David C. Folch, Daniel Arribas-Bel, Julia Koschinsky, and Seth E. Spielman. Spatial Variation in the Quality of American Community Survey Estimates. *Demography*, 53(5):1535–1554, October 2016. ISSN 0070-3370, 1533-7790. doi: 10.1007/s13524-016-0499-1. URL `https://read.dukeupress.edu/demography/article/53/5/1535/167641/Spatial-Variation-in-t`

Alexandra Heaney, Jennifer D. Stowell, Jia Coco Liu, Rupa Basu, Miriam Marlier, and Patrick Kinney. Impacts of Fine Particulate Matter From Wildfire Smoke on Respiratory and Cardiovascular Health in California. *GeoHealth*, 6(6), June 2022. ISSN 2471-1403, 2471-1403. doi: 10.1029/2021GH000578. URL `https://onlinelibrary.wiley.com/doi/10.1029/2021GH000578`.

Henderson Sarah B., Brauer Michael, MacNab Ying C., and Kennedy Susan M. Three Measures of Forest Fire Smoke Exposure and Their Associations with Respiratory and Cardiovascular Health Outcomes in a Population-Based Cohort. *Environmental Health Perspectives*, 119(9):1266–1271, September 2011. doi: 10.1289/ehp.1002288. URL `https://ehp.niehs.nih.gov/doi/full/10.1289/ehp.1002288`.

Steven M. Hollenberg. Understanding stress cardiomyopathy. *Intensive Care Medicine*, 42(3):432–435, March 2016. ISSN 1432-1238. doi: 10.1007/s00134-015-4018-4.

Jamie L. Humphrey, Colleen E. Reid, Ellen J. Kinnee, Laura D. Kubzansky, Lucy F. Robinson, and Jane E. Clougherty. Putting Co-Exposures on Equal Footing: An Ecological Analysis of Same-Scale Measures of Air Pollution and Social Factors on Cardiovascular Disease in New York City. *International Journal of Environmental Research and Public Health*, 16(23):4621, December 2019. ISSN 1661-7827. doi: 10.3390/ijerph16234621. URL `https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6926874/`.

Fay Johnston, Ivan Hanigan, Sarah Henderson, Geoffrey Morgan, and David Bowman. Extreme air pollution events from bushfires and dust storms and their association with mortality in Sydney, Australia 1994–2007. *Environmental Research*, 111 (6):811–816, August 2011. ISSN 0013-9351. doi: 10.1016/j.envres.2011.05.007. URL `https://www.sciencedirect.com/science/article/pii/S0013935111001241`.

Fay H Johnston, Stuart Purdie, Bin Jalaludin, Kara L Martin, Sarah B Henderson, and Geoffrey G Morgan. Air pollution events from forest fires and emergency department attendances in Sydney, Australia 1996–2007: a case-crossover analysis. *Environmental Health*, 13:105, December 2014. ISSN 1476-069X. doi: 10.1186/1476-069X-13-105. URL `https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4271508/`.

Hannah T. Jordan, Steven D. Stellman, Alfredo Morabia, Sara A. Miller-Archie, Howard Alper, Zoey Laskaris, Robert M. Brackbill, and James E. Cone. Cardiovascular Disease Hospitalizations in Relation to Exposure to the September 11, 2001 World Trade Center Disaster and Posttraumatic Stress Disorder. *Journal of the American Heart Association: Cardiovascular and Cerebrovascular Disease*, 2 (5), October 2013. ISSN 2047-9980. doi: 10.1161/JAHA.113.000431. URL `https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3835258/`.

Lotte Kaasenbrood, S. Matthijs Boekholdt, Yolanda van der Graaf, Kausik K. Ray, Ron J. G. Peters, John J. P. Kastelein, Pierre Amarenco, John C. LaRosa, Maarten J. M. Cramer, Jan Westerink, L. Jaap Kappelle, Gert J. de Borst, and Frank L. J. Visseren. Distribution of Estimated 10-Year Risk of Recurrent Vascular Events and Residual Risk in a Secondary Prevention Population. *Circulation*, 134(19):1419–1429, November 2016. ISSN 1524-4539. doi: 10.1161/CIRCULATIONAHA.116.021314.

A. J. Kerr, J. Broad, S. Wells, T. Riddell, and R. Jackson. Should the first priority in cardiovascular risk management be those with prior cardiovascular disease? *Heart*, 95 (2):125–129, January 2009. ISSN 1355-6037, 1468-201X. doi: 10.1136/hrt.2007.140905. URL `https://heart.bmj.com/content/95/2/125`. Publisher: BMJ Publishing Group Ltd Section: Original article.

John P. Klein and Melvin L. Moeschberger. *Survival analysis: techniques for censored and truncated data*. Statistics for biology and health. Springer, New York, NY, 2. ed., corr. 3. print edition, 2010. ISBN 978-0-387-21645-4 978-1-4419-2985-3.

J. Leor and R. A. Kloner. The Northridge earthquake as a trigger for acute myocardial infarction. *The American Journal of Cardiology*, 77(14):1230–1232, June 1996. ISSN 0002-9149.

Judith H. Lichtman, Erica C. Leifheit-Limson, Sara B. Jones, Yun Wang, and Larry B. Goldstein. Average Temperature, Diurnal Temperature Variation, and Stroke Hospitalizations. *Journal of Stroke and Cerebrovascular Diseases*, 25(6):1489–1494, June 2016. ISSN 1052-3057. doi: 10.1016/j.jstrokecerebrovasdis.2016.02.037. URL `http://www.sciencedirect.com/science/article/pii/S1052305716001427`.

Youn-Hee Lim, Yun-Chul Hong, and Ho Kim. Effects of diurnal temperature range on cardiovascular and respiratory hospital admissions in Korea. *Science of The Total Environment*, 417-418:55–60, February 2012. ISSN 0048-9697. doi: 10.1016/j.scitotenv.2011.12.048. URL `http://www.sciencedirect.com/science/article/pii/S0048969711015142`.

David Moore, Ray Copes, Robert Fisk, Ruth Joy, Keith Chan, and Michael Brauer. Population health effects of air quality changes due to forest fires in British Columbia in 2003: estimates from physician-visit billing data. *Canadian Journal of Public Health = Revue Canadienne De Sante Publique*, 97(2):105–108, April 2006. ISSN 0008-4263.

Joshua A. Mott, David M. Mannino, Clinton J. Alverson, Andrew Kiyu, Jamilah Hashim, Tzesan Lee, Kenneth Falter, and Stephen C. Redd. Cardiorespiratory hospitalizations associated with smoke exposure during the 1997, Southeast Asian forest fires. *International Journal of Hygiene and Environmental Health*, 208(1-2):75–85, 2005. ISSN 1438-4639. doi: 10.1016/j.ijheh.2005.01.018.

I. Nakagawa, K. Nakamura, M. Oyama, O. Yamazaki, K. Ishigami, Y. Tsuchiya, and M. Yamamoto. Long-term effects of the Niigata-Chuetsu earthquake in Japan on acute myocardial infarction mortality: an analysis of death certificate data. *Heart*, 95(24):2009–2013, December 2009. ISSN 1355-6037, 1468-201X. doi: 10.1136/hrt.2009.174201. URL `https://heart.bmj.com/content/95/24/2009`.

Akihiro Nakamura, Hiroyuki Satake, Akiyo Abe, Yuta Kagaya, Katuya Kohzu, Kenjiro Sato, Sohta Nakajima, Shigefumi Fukui, Hideaki Endo, Tohru Takahashi, Eiji Nozaki, and Kenji Tamaki. Characteristics of heart failure associated with the Great East Japan Earthquake. *Journal of Cardiology*, 62(1):25–30, July 2013. ISSN 1876-4738. doi: 10.1016/j.jjcc.2013.02.015.

NOAA OSPO HMS. National oceanic and atmospheric administration office of satellite and product operations hazard mapping system, Jan 2018. URL `https://www.ospo.noaa.gov/Products/land/hms.htmldata.`

Matthew N. Peters, John C. Moscona, Morgan J. Katz, Kevin B. Deandrade, Henry C. Quevedo, Sumit Tiwari, Andrew R. Burchett, Thomas A. Turnage, Kanwar Y. Singh, Edmond N. Fomunung, Sudesh Srivastav, Patrice Delafontaine, and Anand M. Irimpen. Natural disasters and myocardial infarction: the six years after Hurricane Katrina. *Mayo Clinic Proceedings*, 89(4):472–477, April 2014. ISSN 1942-5546. doi: 10.1016/j.mayocp.2013.12.013.

QGIS Development Team. *QGIS Geographic Information System*. Open Source Geospatial Foundation, 2009. URL `http://qgis.osgeo.org`.

R Core Team. *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria, 2022. URL `https://www.R-project.org/`.

Colleen E. Reid and Melissa May Maestas. Wildfire smoke exposure under climate change: impact on respiratory health of affected communities. *Current Opinion in Pulmonary Medicine*, 25(2):179–187, March 2019. ISSN 1531-6971. doi: 10.1097/MCP.0000000000000552.

Colleen E. Reid, Michael Jerrett, Maya L. Petersen, Gabriele G. Pfister, Philip E. Morefield, Ira B. Tager, Sean M. Raffuse, and John R. Balmes. Spatiotemporal prediction of fine particulate matter during the 2008 northern California wildfires using machine learning. *Environmental Science & Technology*, 49(6):3887–3896, March 2015. ISSN 1520-5851. doi: 10.1021/es505846r.

Colleen E. Reid, Michael Brauer, Fay H. Johnston, Michael Jerrett, John R. Balmes, and Catherine T. Elliott. Critical Review of Health Impacts of Wildfire Smoke Exposure. *Environmental Health Perspectives*, 124(9):1334–1343, 2016a. ISSN 1552-9924. doi: 10.1289/ehp.1409277.

Colleen E. Reid, Michael Jerrett, Ira B. Tager, Maya L. Petersen, Jennifer K. Mann, and John R. Balmes. Differential respiratory health effects from the 2008 northern California wildfires: A spatiotemporal approach. *Environmental Research*, 150:227–235, 2016b. ISSN 1096-0953. doi: 10.1016/j.envres.2016.06.012.

Colleen E. Reid, Ellen M. Considine, Gregory L. Watson, Donatello Telesca, Gabriele G. Pfister, and Michael Jerrett. Associations between respiratory health and ozone and fine particulate matter during a wildfire event. *Environment International*, 129:291–298, August 2019. ISSN 1873-6750. doi: 10.1016/j.envint.2019.04.033.

Benjamin Ryan, Richard C. Franklin, Frederick M. Burkle, Peter Aitken, Erin Smith, Kerrianne Watt, and Peter Leggat. Identifying and Describing the Impact of Cyclone, Storm and Flood Related Disasters on Treatment Management, Care and Exacerbations of Non-communicable Diseases and the Implications for Public Health. *PLoS currents*, 7, September 2015. ISSN 2157-3999.

Seth E. Spielman and Eun-hye Yoo. The spatial dimensions of neighborhood effects. *Social Science & Medicine*, 68(6):1098–1105, March 2009. ISSN 02779536. doi: 10.1016/j.socscimed.2008.12.048. URL `https://linkinghub.elsevier.com/retrieve/pii/S027795360800693X`.

Seth E. Spielman, David Folch, and Nicholas Nagle. Patterns and causes of uncertainty in the American Community Survey. *Applied Geography*, 46:147–157, January 2014. ISSN 01436228. doi: 10.1016/j.apgeog.2013.11.002. URL `https://linkinghub.elsevier.com/retrieve/pii/S0143622813002518`.

Joel N. Swerdel, Teresa M. Janevic, Nora M. Cosgrove, John B. Kostis, and Myocardial Infarction Data Acquisition System (MIDAS 24) Study Group. The effect of Hurricane

Sandy on cardiovascular events in New Jersey. *Journal of the American Heart Association*, 3(6):e001354, December 2014. ISSN 2047-9980. doi: 10.1161/JAHA.114.001354.

Terry M. Therneau and Patricia M. Grambsch. *Modeling Survival Data: Extending the Cox Model*. Springer, New York, 2000. ISBN 0-387-98784-3.

Brian Thelen, Nancy HF French, Benjamin W. Koziol, Michael Billmire, Robert Chris Owen, Jeffrey Johnson, Michele Ginsberg, Tatiana Loboda, and Shiliang Wu. Modeling acute respiratory illness during the 2007 San Diego wildland fires using a coupled emissions-transport system and generalized additive modeling. *Environmental Health*, 12(1):94, November 2013. ISSN 1476-069X. doi: 10.1186/1476-069X-12-94. URL `https://doi.org/10.1186/1476-069X-12-94`.

Terry M Therneau. *A Package for Survival Analysis in R*, 2021. URL `https://CRAN.R-project.org/package=survival`. R package version 3.2-13.

Connie W. Tsao, Aaron W. Aday, Zaid I. Almarzooq, Cheryl A.M. Anderson, Pankaj Arora, Christy L. Avery, Carissa M. Baker-Smith, Andrea Z. Beaton, Amelia K. Boehme, Alfred E. Buxton, Yvonne Commodore-Mensah, Mitchell S.V. Elkind, Kelly R. Evenson, Chete Eze-Nliam, Setri Fugar, Giuliano Generoso, Debra G. Heard, Swapnil Hiremath, Jennifer E. Ho, Rizwan Kalani, Dhruv S. Kazi, Darae Ko, Deborah A. Levine, Junxiu Liu, Jun Ma, Jared W. Magnani, Erin D. Michos, Michael E. Mussolino, Sankar D. Navaneethan, Nisha I. Parikh, Remy Poudel, Mary Rezk-Hanna, Gregory A. Roth, Nilay S. Shah, Marie-Pierre St-Onge, Evan L. Thacker, Salim S. Virani, Jenifer H. Voeks, Nae-Yuh Wang, Nathan D. Wong, Sally S. Wong, Kristine Yaffe, Seth S. Martin, and on behalf of the American Heart Association Council on Epidemiology and Prevention Statistics Committee and Stroke Statistics Subcommittee. Heart Disease and Stroke Statistics—2023 Update: A Report From the American Heart Association. *Circulation*, 147(8), February 2023. ISSN 0009-7322, 1524-4539. doi: 10.1161/CIR.0000000000001123. URL `https://www.ahajournals.org/doi/10.1161/CIR.0000000000001123`.

Gregory A. Wellenius, Joel Schwartz, and Murray A. Mittleman. Air pollution and hospital admissions for ischemic and hemorrhagic stroke among medicare beneficiaries. *Stroke*, 36(12):2549–2553, December 2005. ISSN 1524-4628. doi: 10.1161/01.STR.0000189687.78760.47.

Bo Wen, Yao Wu, Rongbin Xu, Yuming Guo, and Shanshan Li. Excess emergency department visits for cardiovascular and respiratory diseases during the 2019-20 bushfire period in Australia: A two-stage interrupted time-series analysis. *The Science of the Total Environment*, 809:152226, February 2022. ISSN 1879-1026. doi: 10.1016/j.scitotenv.2021.152226.

Graham Wesolowski. Regional Wildfire Mitigation Program, 2021. URL `https://rwmpsantabarbara.org/`.

Zachary S. Wettstein, Sumi Hoshiko, Jahan Fahimi, Robert J. Harrison, Wayne E. Cascio, and Ana G. Rappold. Cardiovascular and Cerebrovascular Emergency Department Visits Associated With Wildfire Smoke Exposure in California in 2015. *Journal* *of the American Heart Association*, 7(8):e007492, April 2018. ISSN 2047-9980. doi: 10.1161/JAHA.117.007492.

World Health Organization. A conceptual framework for action on the social determinants of health. page 76, 2010. ISSN 9789241500852. URL https://apps.who.int/iris/handle/10665/44489. Place: Geneva Publisher: World Health Organization.

Jun Yang, Maigeng Zhou, Chun-Quan Ou, Peng Yin, Mengmeng Li, Shilu Tong, Antonio Gasparrini, Xiaobo Liu, Jing Li, Lina Cao, Haixia Wu, and Qiyong Liu. Seasonal variations of temperature-related mortality burden from cardiovascular disease and myocardial infarction in China. *Environmental Pollution*, 224: 400–406, May 2017. ISSN 0269-7491. doi: 10.1016/j.envpol.2017.02.020. URL http://www.sciencedirect.com/science/article/pii/S0269749116322680.

7 Tables and Figures

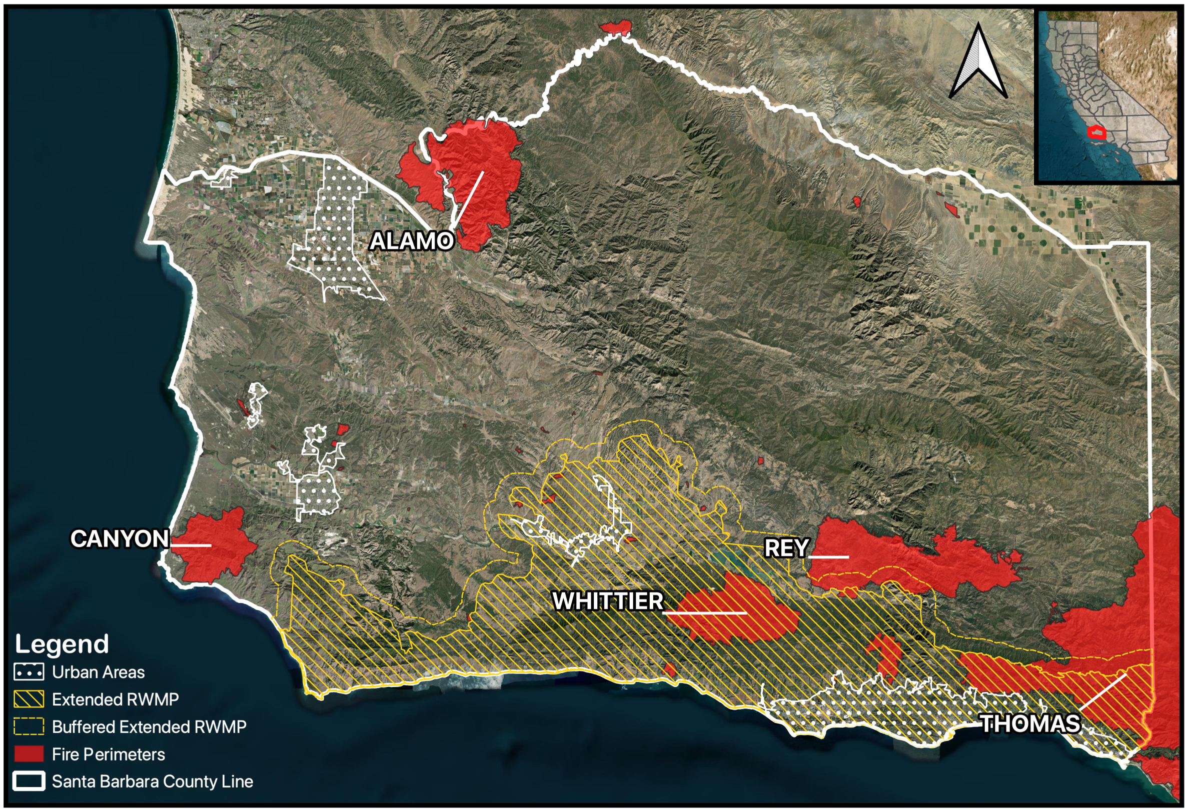


Figure 1: This map displays the final named wildfire perimeters during the 2016-2019 period in Santa Barbara County (red polygons) as well as the 2010 Census classified urban areas (white dotted pattern polygon). An urban area classification signifies an area with a density greater than 50,000 people and is derived from the United State 2010 Census. The extended Regional Wildfire Mitigation Program (RWMP) area is also displayed (yellow hash polygon). Additionally, the extended RWMP area was buffered by 1600 meters (solid yellow line) in the analysis. The underlying base map is ESRI Satellite Data, freely available. These data were mapped by the author on December 19, 2022. Note, only fires with areas greater than 10,000 acres are labeled on the map.

Patient Population Criteria	
Patients with any of the following ICD-10 diagnosis codes as a “New Diagnosis” within the time period. All diagnosis codes should appear as primary or secondary codes within the problem list of the EMR. $*$ Indicates wildcard (all available next-digit options), in addition to parent codes.	
ICD-10-CM Code	**Description**
I10	Essential Primary Hypertension
I11.*	Hypertensive Heart Disease
I13.**	Hypertensive Heart and Chronic Kidney Disease
I16.*	Hypertensive Crisis
I20.*	Angina Pectoris
I21.**	Acute Myocardial Infarction
I22.*	Subsequent ST elevation (STEMI) and non-ST elevation (NSTEMI) myocardial infarction
I23.*	Certain current complications following ST elevation and non-ST elevation myocardial infarction within 28 day period
I24.*	Other acute ischemic heart diseases
I25.***	Chronic Ischemic Heart Disease
I40.*	Acute Myocarditis
I42.*	Cardiomyopathy
143.*	Cardiomyopathy in disease classified elsewhere
I44.**	Atrioventricular and left bundle-branch blocks
I45.**	Other conduction disorders
I46.*	Cardiac arrest
I47.*	Paroxysmal tachycardia
I48.**	Atrial fibrillation and flutter
I49.**	Other cardiac arrhythmias
I50.**	Heart Failure
I51.**	Complications and ill-defined descriptions of heart disease
I52	Other heart disorders in diseases classified elsewhere
I71.**	Aortic aneurysm and dissection
R00.*	Abnormalities of heart beat
R07.1	Chest pain on breathing
R07.2	Precordial pain
R07.8*	Other chest pain
R07.9	Chest pain, unspecified
R94.3*	Abnormal results of cardiovascular function studies

Table 1: Table describes the International Classification of Diseases, Tenth Revision, Clinical Modification (ICD-10-CM) diagnosis codes that comprise the qualifying cardiac events within the study time frame. Note that $*$ indicates depth of wildcard parent and child-nodes pursued. This list was compiled and revised for completeness and clinical relevance by all clinical team members.

Sample Characteristics			
Variable		Evacuation Exposed % (n)	Evacuation Unexposed % (n)
		16.2 (391)	83.8 (2020)
Sex	Female	41.2 (161)	39.2 (792)
	Male	58.8 (230)	60.8 (1228)
Diabetic Status	None	86.4 (338)	84.9 (1715)
	Present	13.6 (53)	15.1 (305)
Smoking Status	None	94.4 (369)	95.1 (1922)
	Present	5.6 (22)	4.9 (98)
History of Heart Surgery	None	85.7 (335)	83.6 (1689)
	Present	14.3 (56)	16.4 (331)
Preferred Language	English	86.7 (339)	89.4 (1805)
	Other	0.3 (1)	1.1 (22)
	Spanish	13.0 (51)	9.6 (193)
Insurance Type	Commercial	18.2 (71)	18.6 (376)
	Other	17.1 (67)	15.3 (310)
	Senior	64.7 (253)	66.0 (1334)
Age Category	< 60	22.0 (86)	23.4 (473)
	60s	19.9 (78)	23.2 (469)
	70s	33.0 (129)	31.0 (626)
	≥ 80	25.1 (98)	22.4 (452)
Mean Age (Years)	At 12/05/2017	69.5	68.4
Mean Length of Stay (Days)	At Qualifying Event	5.2	5.0

Table 2: Descriptive attributes of patients with a qualifying cardiovascular event within the study period. No significant differences between evacuated individual and non-evacuated individuals were observed at $\alpha = 0.1$.

	Dependent variable:				
	Risk of Secondary CVE (Robust Errors)				
	(1)	(2)	(3)	(4)	(5)
Evacuation	0.124	0.137	0.118	0.151	0.125
	(0.153)	(0.154)	(0.157)	(0.163)	(0.155)
1-Day Smoke Exposure		*Thin Plume*	*Medium Plume*	*Thick Plume*	*Any Plume*
		−0.162	0.028	−0.089	−0.006
		(0.134)	(0.144)	(0.144)	(0.136)
Sex: Male	0.015	0.015	0.015	0.015	0.015
	(0.103)	(0.102)	(0.103)	(0.103)	(0.103)
Age Category: 60s	0.367**	0.369**	0.366**	0.368**	0.367**
	(0.177)	(0.177)	(0.177)	(0.177)	(0.177)
Age Category: 70s	0.636***	0.636***	0.636***	0.633***	0.636***
	(0.192)	(0.192)	(0.192)	(0.192)	(0.192)
Age Category: >80	0.696***	0.692***	0.696***	0.692***	0.696***
	(0.203)	(0.202)	(0.203)	(0.203)	(0.203)
Insurance Type: Other	1.058***	1.053***	1.058***	1.055***	1.057***
	(0.204)	(0.205)	(0.205)	(0.205)	(0.205)
Insurance Type: Senior	0.528**	0.534***	0.527**	0.531**	0.528**
	(0.207)	(0.206)	(0.207)	(0.207)	(0.207)
Preferred Language: Other	−1.566*	−1.538*	−1.568*	−1.559*	−1.565*
	(0.897)	(0.903)	(0.895)	(0.897)	(0.897)
Preferred Language: Spanish	−0.051	−0.043	−0.052	−0.048	−0.051
	(0.155)	(0.155)	(0.155)	(0.155)	(0.155)
History of Heart Surgery	0.191	0.191	0.191	0.190	0.191
	(0.131)	(0.131)	(0.131)	(0.131)	(0.131)
History of Diabetes	0.873***	0.864***	0.874***	0.869***	0.872***
	(0.108)	(0.109)	(0.108)	(0.108)	(0.109)
History of Smoking	0.606***	0.608***	0.606***	0.607***	0.606***
	(0.189)	(0.190)	(0.189)	(0.190)	(0.189)
N_{Total}	2411	2411	2411	2411	2411
$N_{\text{Evacuation Exposed}}$	391	391	391	391	391
$N_{\text{Smoke Exposed}}$	0	1533	1614	1425	1649
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 3: Full Covariate Models with Evacuation and Mixed Density Smoke Exposures

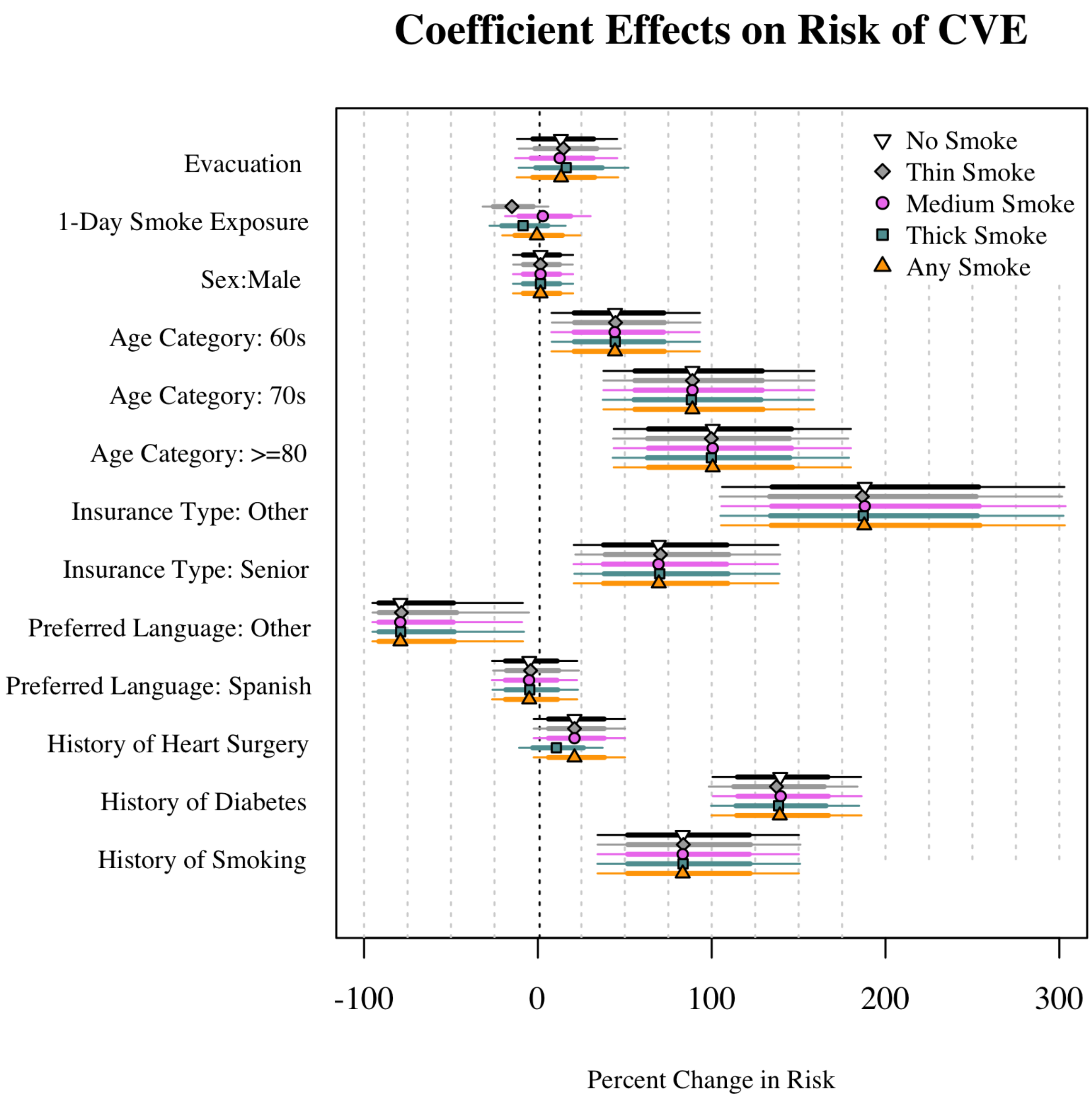
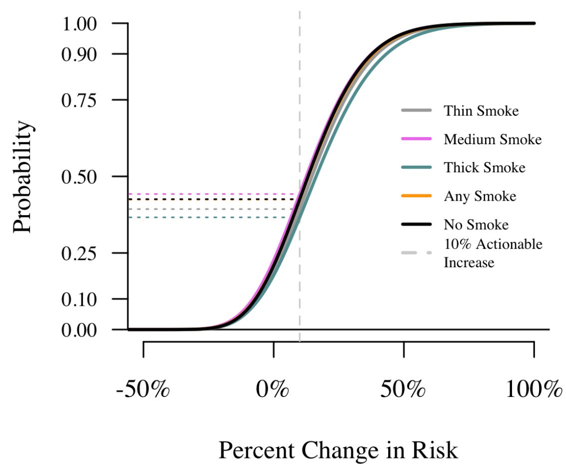
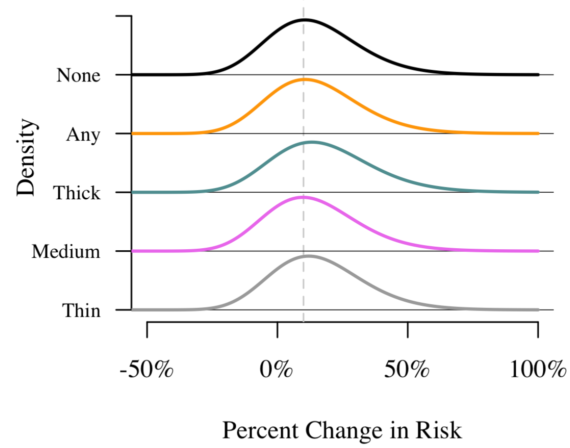


Figure 2: The coefficient effects on secondary CVE risk are summarized for each smoke type in this figure. The 90% confidence intervals are shown in addition to 68.5% confidence intervals and the the point estimates. Note that the 68.5% confidence intervals show one-standard deviation from the parameter estimate mean in either direction. The coloring indicates parameter estimates under 1-day of the various smoke specifications: thin smoke exposure (grey), medium smoke exposure (pink), thick smoke exposure (blue-green), and any smoke exposure (orange). The point estimates for evacuation order effects are 14.7% (thin), 12.5% (medium), 16.3% (thick) and 13.3% (any) increase in risk over the baseline.



(a) Cumulative Distribution of Estimates



(b) Density of Estimates

Figure 3: Panel (a) displays the cumulative distributions corresponding to the evacuation parameter estimates from the fitted models presented in Table 3, and displayed in Figure 2. The dotted vertical line shows a 10% increase in risk of CVE, and the the corresponding probability quantiles are shown on the y-axis. The quantiles range from 0.36 to 0.44 indicating the probability of the percent change in CVE risk being 10% or less. Panel (b) displays the densities for each evacuation order parameter estimate, with the 10% increase also marked. Under each specification more than 50% of the estimate parameter distribution lies to the right of the 10% line.

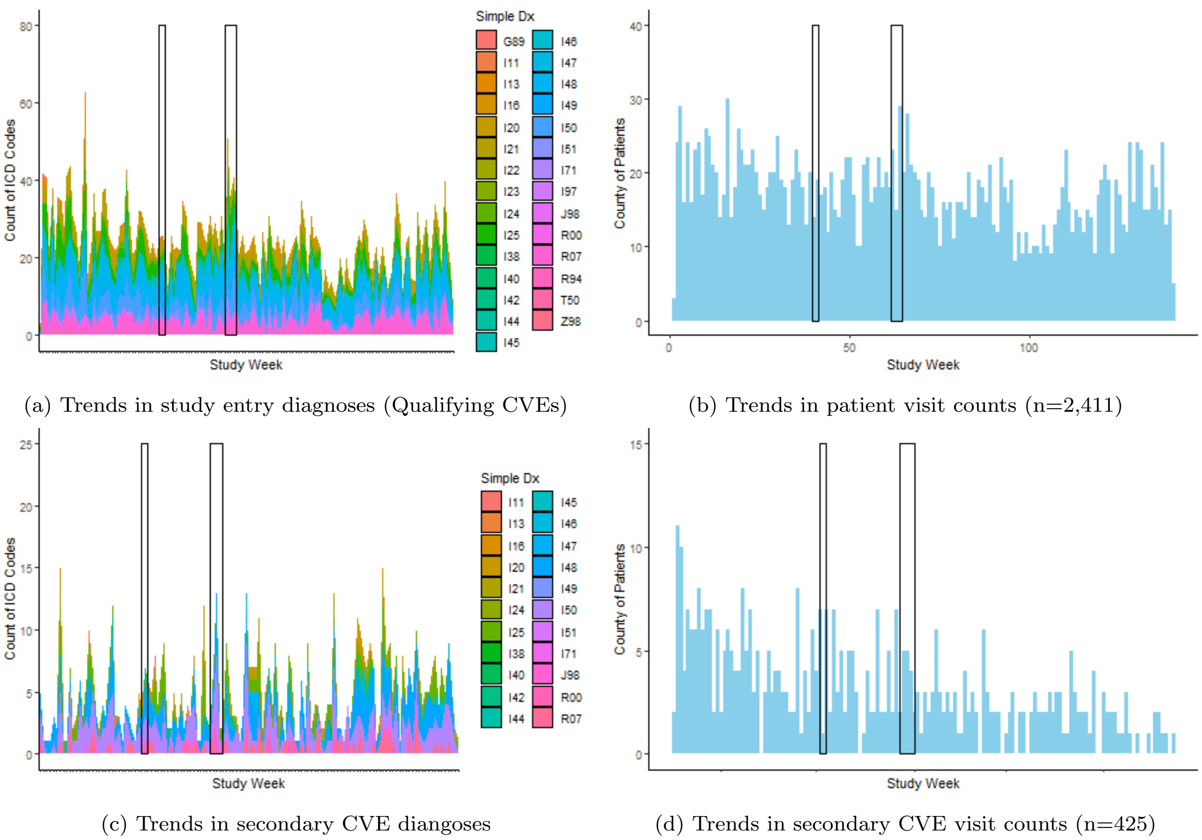
7.1.1 Visit and Diagnoses Trends

Figure 4 (a) shows the trends in diagnosis code use over the study period. The black rectangles indicate the periods of active evacuation orders for the Alamo, Whittier, and Thomas fires. The Alamo and Whittier fire evacuation orders occurred concurrently (first fire period), whereas the Thomas fire burned longer and more area, and subsequently had more associated evacuation orders. There is an increase in diagnoses in this period, which is echoed in the unique patient accrual counts in figure 4 (b).

Because of the study design, patients could enter the study with a qualifying cardiac event at any point and are followed through to censorship (study end) or their secondary CVE. The arrival counts for each study week range from 10 to 38, and the arrival pattern suggests both a relatively high variability in weekly case counts for new CVE as well as some potential seasonal trends. The Thomas fire began in early December (study week 62), a period where other studies(Lichtman et al., 2016, Yang et al., 2017) suggest a seasonal increase in cardiac events like acute myocardial infarction and stroke. Comparing the mean arrival rate for new cardiac events from December 1, 2017 - January 15, 2018 with the mean arrival rates for the same period the year prior and the year post, we do not see a significant difference in arrival rate the year prior, and we see a significant decrease from the following year.[11]

The diagnoses patterns and trends for the second CVEs (n=474) are similarly presented in figure 4 (c). The most common diagnoses codes for those returning to the hospital are heart failure (45.4% of patients), atrial fibrillation and flutter (40.5%), followed by chronic ischemic heart disease (19.8%). In contrast to the first cardiac event diagnosis trends over time, the trends of the second cardiac event diagnoses appear more scattered and random, without an obvious seasonality. The visit counts are also sporadic through the study period (see figure 4 (d)).

[11] Year prior had a mean arrival rate of 3.8 patients per day and the Thomas fire year had an average arrival rate of 3.6, (two-sided t-test, p-value = 0.58). The year following the Thomas fire had an average arrival rate of 2.8 (two-sided t-test, p-value = 0.07).



(a) Trends in study entry diagnoses (Qualifying CVEs)

(b) Trends in patient visit counts (n=2,411)

(c) Trends in secondary CVE diangoses

(d) Trends in secondary CVE visit counts (n=425)

Figure 4: The upper row of this graphic shows the trends of parent ICD-10 diagnosis codes within qualifying CVEs for first-time patients within Cottage Hospital over the study period (a) and the corresponding new patient visit counts on the right (b). For example, I46 indicates visits for cardiac arrest and includes visits for child codes: I46.2 cardiac arrest due to underlying cardiac condition, I46.8 cardiac arrest due to other underlying condition and I46.9 cardiac arrest, cause unspecified. The lower row shows the trends of diagnosis codes for secondary CVEs (c) and the patient visit counts on the right (d). Many patients presented with (or acquired) more than one diagnosis in their admission. However, patient visit counts directly correspond to a single patient within the study; no patient appeared more than twice. The large vertical rectangles indicate the weeks that evacuation orders were active for the Alamo and Whittier fires (concurrent evacuation orders, first rectangle), and the Thomas fire (second rectangle). There appears to be an elevated count of new patients around the time of the Thomas fire and the mean rate of arrival is significantly elevated when compared to the year post fire ($p < 0.1$), but not when compared to the year prior to the fire ($p = 0.5$).

7.1.2 Mixed Density Smoke Models Without Evacuation Variable

Table 4 shows the coefficient estimates for mixed density 1-day cumulative models (no plume, thin plume, medium plume, thick plume). Estimates for the electronic medical record driven covariates remain consistent with the estimates from models including the evacuation exposure (see Table 3). Estimates for each smoke exposure also remain quite similar in direction and magnitude, though ‘Any Plume‘ exposure flipped signs. To the authors this suggests a lack of evidence relating 1-day cumulative smoke exposure to secondary CVE risk.

	Dependent Variable:				
	Risk of Secondary CVE (Robust Errors)				
	No Plume	Thin Plume	Medium Plume	Thick Plume	Any Plume
1-Day Smoke Exposure		−0.154	0.043	−0.055	0.006
		(0.133)	(0.141)	(0.136)	(0.133)
Sex: Male	0.015	0.014	0.015	0.014	0.015
	(0.103)	(0.102)	(0.103)	(0.103)	(0.103)
Age Category: 60s	0.368**	0.370**	0.367**	0.370**	0.368**
	(0.177)	(0.177)	(0.177)	(0.177)	(0.177)
Age Category: 70s	0.639***	0.639***	0.638***	0.637***	0.639***
	(0.192)	(0.192)	(0.192)	(0.192)	(0.192)
Age Category: >80	0.697***	0.694***	0.698***	0.695***	0.698***
	(0.203)	(0.203)	(0.203)	(0.204)	(0.203)
Insurance Type: Other	1.061***	1.057***	1.061***	1.059***	1.061***
	(0.205)	(0.205)	(0.205)	(0.205)	(0.205)
Insurance Type: Senior	0.529**	0.535***	0.528**	0.531**	0.528**
	(0.207)	(0.206)	(0.207)	(0.207)	(0.207)
Preferred Language: Other	−1.574*	−1.549*	−1.577*	−1.571*	−1.575*
	(0.897)	(0.903)	(0.895)	(0.897)	(0.897)
Preferred Language: Spanish	−0.046	−0.038	−0.048	−0.043	−0.046
	(0.155)	(0.155)	(0.155)	(0.155)	(0.155)
History of Heart Surgery	0.189	0.190	0.189	0.188	0.189
	(0.131)	(0.131)	(0.131)	(0.131)	(0.131)
History of Diabetes	0.869***	0.861***	0.871***	0.866***	0.870***
	(0.108)	(0.109)	(0.108)	(0.108)	(0.109)
History of Smoking	0.608***	0.610***	0.608***	0.608***	0.608***
	(0.190)	(0.190)	(0.189)	(0.190)	(0.190)
N_{Total}	2411	2411	2411	2411	2411
$N_{\text{Smoke Exposed}}$	0	1533	1614	1425	1649
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 4: Mixed Density Smoke Models with No Evacuation (Robust Errors)