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Applying a two-stage generalized synthetic control approach to quantify the heterogeneous health effects of extreme weather events

A 2018 large wildfire in California event as a case study

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Abstract: Extreme weather events, including wildfires, are becoming more intense, frequent, and expansive due to climate change, thus increasing negative health outcomes. However, such effects can vary across space, time, and population subgroups, requiring methods that can handle multiple exposed units, account for time-varying confounding, and capture heterogeneous treatment effects. In this article, we proposed an approach based on staggered generalized synthetic control methods to study heterogeneous health effects, using the 2018 California wildfire season as a case study. This study aimed to estimate the effects of the November 2018 California wildfires, one of the state's deadliest and most destructive wildfire seasons, on respiratory and circulatory health, document heterogeneity in health impacts, and investigate drivers of this heterogeneity. We applied a two-stage generalized synthetic control method to compare health outcomes in exposed (from 8 November to 5 December 2018) versus unexposed counties and used random-effects meta-regression to evaluate the effect modification of county-level socioeconomic variables on the observed health effects of the November 2018 wildfires. We observed an increase in respiratory hospitalizations for most exposed counties when compared with unexposed counties, with significant increases in Fresno, San Francisco, San Joaquin, San Mateo, and Santa Clara counties. No effect on circulatory hospitalizations was observed. County-level sociodemographic characteristics seem to not modulate the effects of wildfire smoke on respiratory hospitalizations. This novel two-stage framework can be applied in broader settings to understand spatially and temporally compounded health impacts of climate hazards. We provide codes in R for reproducibility and replication purposes.

Keywords: Quasi-experimental method; Heterogeneous effect; Environmental justice; Climate hazards; Air pollution

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Data and codes for reproducibility and replication purposes are available at the following link: https://github.com/benmarhnia-lab/Wildfires_social_vulnerability.

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Introduction

Wildfires are becoming increasingly intense, frequent, and expansive as a result of climate change, particularly in the western United States.¹⁻⁴ One result of this increased wildfire activity is an increase in air pollution coming from wildfire smoke, with drastic spikes in wildfire-associated PM_{2.5} concentration (particulate matter with an aerodynamic diameter $\leq 2.5 \mu\text{m}$).⁵ In fact, this increase in wildfire PM_{2.5} pollution has effectively reversed decades of PM_{2.5} air quality improvements achieved through policy changes across the country, particularly in the western states.^{5,6} This offsetting of public health gains has also been specifically observed within the state of California.⁷

Wildfire-associated PM_{2.5} emissions contribute to negative health outcomes, with previous studies documenting the effects

What this study adds:

This study demonstrated the utility of a two-stage generalized synthetic control method as an alternative to traditional approaches for studying the impacts of extreme events such as wildfires. We proposed a framework based on this novel quasi-experimental method to quantify the heterogeneous health effects of the 2018 California wildfires and identify its potential drivers. Such a framework can be used to understand spatially and temporally compounded health impacts of climate hazards, such as heat waves or flooding events. Understanding the drivers of the heterogeneous effects of climate-sensitive exposures is crucial to designing adaptation and emergency response strategies that prioritize vulnerable communities.

on respiratory and cardiovascular health.^{8–15} Evidence suggests that PM_{2.5} emitted from wildfires may be more harmful to human health than equivalent amounts of PM_{2.5} emitted from more traditional sources of pollution (e.g., traffic, agricultural, or industrial sources).^{16–18} In addition, the contribution of wildfire smoke PM_{2.5} emissions to all PM_{2.5} emissions continues to increase,⁶ intensifying the health impacts of wildfires.

There is also a growing body of evidence that wildfire smoke may not impact all population subgroups equally. Several studies, using various measures, have found that wildfire smoke-related health outcomes differ based on socioeconomic status (SES), with worse outcomes for those in lower SES groups.^{11,19–22} Differential health outcomes from wildfire events have also been found between communities of differing race/ethnicity.^{7,20,21,23} For instance, Liu et al²⁰ found that Black Americans face a higher risk of respiratory hospitalizations from wildfire events than White Americans. In California, communities of color and communities of lower SES are at higher risk of being exposed to harmful compounding poor air quality events from wildfires and heatwaves.²⁴ Age is also an effect modifier of wildfire PM_{2.5} health impacts, with the very young and the elderly being most at risk.^{7,8,14,25–27} In this context, adaptation may be more difficult for communities and individuals of lower SES due to disparities in access to resources and care, health literacy, or simply being more likely to live near an exposure source or other sources of pollution,^{20,28,29} hence the heightened vulnerability these communities often face.

Besides heterogeneity across population subgroups, wildfire smoke health impacts may also differ spatially and temporally. Understanding the drivers of such variability may be useful to inform adaptation strategies and also to better understand the mechanisms through which wildfire smoke impacts population health. In this study, we propose a framework based on a two-stage generalized synthetic control (GSC) method to quantify the heterogeneous health effects of wildfire smoke and identify its potential drivers. We use a large wildfire event that took place in 2018 in California and impacted multiple counties as a case study. The 2018 wildfire season was one of the deadliest and most destructive (in terms of area burned) in California's history to date, with several notable fires occurring across the state (though focused most strongly on Northern California), including the Mendocino Complex Fire, the Camp Fire, and the Woolsey Fire.³⁰ The November 2018 Camp Fire caused extensive damage, consuming more than 153,000 acres, resulting in the loss of 85 lives, and the destruction of over 18,000 structures. The total cost of the Camp Fire is estimated at \$16.5 billion.³¹ Simultaneously, Southern California experienced the outbreak of two distinct wildfires known as the Woolsey and Hill Fires, causing a wildfire smoke event, which we find impacted 27 counties. Using our proposed framework, we analyze if respiratory and circulatory health impacts differed across the affected areas and attempt to document the drivers of such heterogeneity. Such a framework can be extended to understanding the temporal variability of wildfire smoke events (i.e., multiple events affecting the same location) and can be used for other climate hazards such as heat waves or flooding events.^{32–34}

We rely on the GSC, a quasi-experimental method (QEM), to study the health effects of the 2018 California wildfires. QEMs are well suited for studying the impacts of extreme events such as wildfires and offer multiple advantages over traditional epidemiologic methods³⁵ as the timing of such events can be assumed to be independent (exogenous) of the time trends of a given health outcome. This allows us to analyze wildfires as a type of natural experiment,³⁶ mimicking randomization and helping reduce the issue of residual confounding, which can be a limitation of more traditional approaches.³⁵ Specifically, GSC has several key advantages, as outlined by Xu³⁷ and Sheridan et al:³⁵ (1) it allows for counterfactuals for each treated unit and allows estimation of heterogeneous treatment effects,

(2) the synthetic control is generalized to be used in the case of multiple treated units or treatment periods, (3) it improves efficiency and interpretability, and (4) it allows one to control for time-varying observed covariates. GSC methods are very useful for studying extreme events such as wildfires, allowing for an alternative approach in situations where it would be impossible to use traditional methods.³⁵ In this study, we extend the GSC method into a two-stage GSC approach to further explore the drivers of heterogeneous effects of extreme weather events.

Therefore, the aim of this study is to apply a two-stage GSC method to determine the effects of the 2018 California wildfires on respiratory and circulatory health, to document the heterogeneity in health impacts, and to explore potential drivers of this heterogeneity. We investigated the effect of modification of socioeconomic and demographic variables on respiratory hospitalizations associated with wildfires.

Methods

Data sources

Hospitalization data for the study came from the patient discharge data and emergency department data collected by the California Department of Health Care Access and Information. We estimated daily counts of respiratory hospitalizations based on the International Classification of Diseases, Tenth Revision (ICD-10-CM) primary diagnosis codes of diseases of the respiratory system (J00–J99) and of cardiovascular hospitalizations based on primary ICD-10 codes of diseases of the circulatory system (I00–I99).³⁸

Wildfire smoke PM_{2.5} data were estimated using an ensemble model based on a multiple imputation approach.³⁹ This model incorporated data from the US Environmental Protection Agency's Air Quality System monitors, aerosol optical depth from NASA satellite measurements, smoke plume observations from the NOAA Hazard Mapping System, meteorological variables from the Gridded Surface Meteorological (gridMET) reanalysis product, and other land-use variables from the National Land Cover Database. The details for this methodology were previously described by Aguilera et al.³⁹ Briefly, Aguilera et al applied a suite of machine learning models, including gradient boosting, random forest, and deep learning, alongside a diverse set of predictors, such as air monitor data, aerosol optical depth, land cover, and meteorological conditions, to estimate ZIP code tabulation areas (ZCTA)-specific daily PM_{2.5} concentrations from all sources. This ensemble model demonstrated high model prediction capabilities with an R^2 of 0.86. Subsequently, they employed a chained random forest algorithm to impute nonwildfire PM_{2.5} concentrations for ZCTA days impacted by smoke plumes. The difference between the ensemble model's estimated daily PM_{2.5} concentrations and the imputed nonwildfire PM_{2.5} concentrations in each ZCTA is defined as wildfire-specific PM_{2.5}. Other meteorological data (including maximum temperature, precipitation, relative humidity, shortwave radiation, and wind velocity) were estimated from the gridMET ~4-km daily dataset. All meteorological data were averaged from zip code level daily estimates to the county level.

County-level sociodemographics for California counties from the 2019 American Community Survey were used for exploring differential vulnerability to wildfire smoke impacts. Variables considered to be important and included in the analysis were the following: population over 55 years and over (%), population over 65 years and over (%), population over 85 years and over (%), median age, population with a high school degree or higher (%), population unemployed (%), median income, population female (%), population non-Hispanic White (%), population non-Hispanic Black (%), population Asian (%), and population Hispanic (%).

Table 1.
Descriptive statistics (mean) of climate exposures and hospitalizations before and after the start of wildfire smoke exposure (8 November) in exposed counties

	Before wildfire (13 September–7 November 2018)		During wildfire (8 November–5 December 2018)	
	Exposed counties (n = 27)	Unexposed counties (n = 31)	Exposed counties (n = 27)	Unexposed counties (n = 31)
Climatic variables				
Mean wildfire smoke PM _{2.5} (µg/m ³)	0.2	3.0	25.5	3.2
Mean max temperature (K)	299.0	297.0	289.8	289.0
Precipitation (mm)	0.4	0.3	4.2	3.9
Specific humidity (g/m ³)	0.0059	0.0055	0.0048	0.0041
Shortwave radiation (W/m ²)	196.1	197.3	106.2	118.3
Wind velocity (m/s)	3.3	3.1	2.9	3.4
Health data				
Mean daily respiratory hospitalizations	265	413	388	512
Mean daily circulatory hospitalizations	168	273	173	282

Stage 1: generalized synthetic control analysis by county

The study period lasted 3 months, from 13 September to 5 December 2018. To quantify the effect of the November 2018 wildfires on hospitalizations in California, a synthetic control approach was used for counties exposed to wildfire smoke during this period. For this case study, a county was considered to be exposed if the average wildfire-PM_{2.5} was higher

than 10 µg/m³ during the exposed period, defined as the 4 weeks following the initial wildfire smoke exposure (i.e., from 8 November to 5 December 2018). No county had more than 10 µg/m³ wildfire-PM_{2.5} in the pre-exposure period, that is, from 13 September to 7 November 2018, levels were 0.2 µg/m³ on average. Therefore, no county was excluded from the analysis because of pre-exposure.

In summary, the GSC methodology is a quasi-experimental approach that uses the timing of the wildfire smoke exposure to quantify its effect.^{35,40} The trend in the “treated” unit, or exposed county, before the wildfire smoke event occurs is used to identify a counterfactual of weighted controls that were not exposed to wildfire smoke. Controls are decomposed with calendar time, lagged outcomes (in the pre-exposure period), and time-varying covariates (including maximum temperature, precipitation, humidity, shortwave radiation, and wind), and an interactive fixed effects model is applied to identify a suitable control based on this time series in the pretreatment period.³⁵ This informs a reweighting approach in which weights for control units are selected based on these decomposed estimates and are used to impute hypothetical trends for the treated unit if they had not been treated by predicting the outcome in the treated unit during the posttreatment period.^{35,37} As a result, each treated unit (i.e., exposed county) has its own synthetic control, which is constructed from a weighted combination of nonexposed counties. Any difference between the treated unit and its synthetic control after the treatment occurs, the Average Treatment Effect among the Treated (ATT), can be attributed to the wildfire smoke event. Covariates included in the GSC model are maximum temperature (K), precipitation (mm), humidity (g/m³), shortwave radiation (W/m²), and wind (m/s).

Regarding our causal identification assumptions,⁴¹ we ensured that: (1) geographical units eligible for the pool of control groups had not been exposed to the smoke event; (2) differences in the incidence rates of hospital admissions between

Zip codes with Smoke week 45–48, 2018

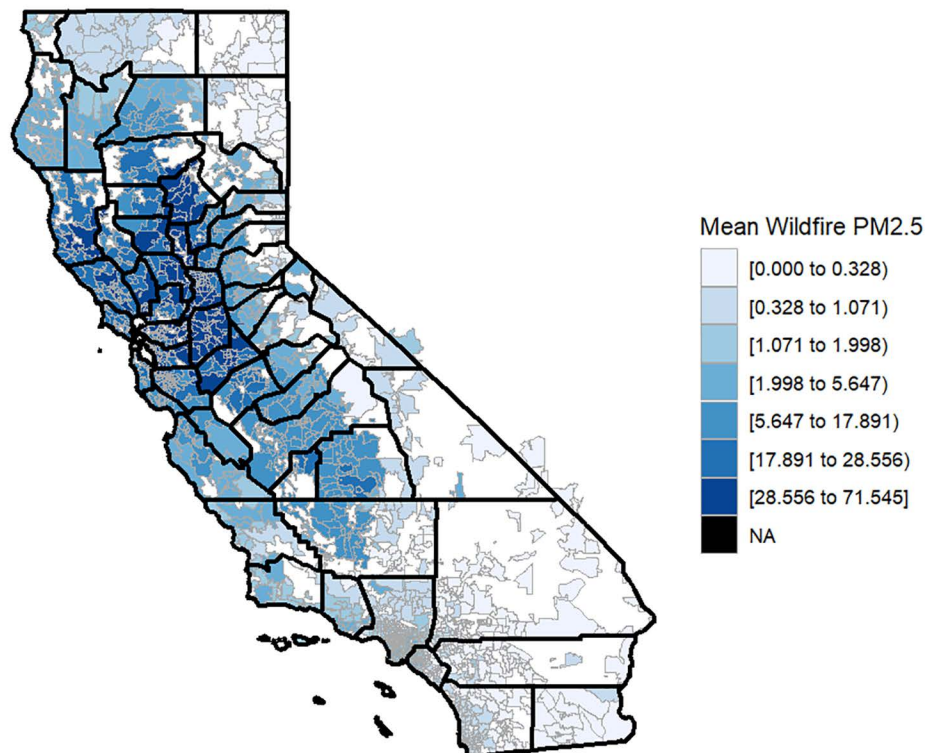


Figure 1. Mean smoke exposure for California zip codes during 2018 wildfires, 8 November–5 December 2018.

Exposed Counties November 2018

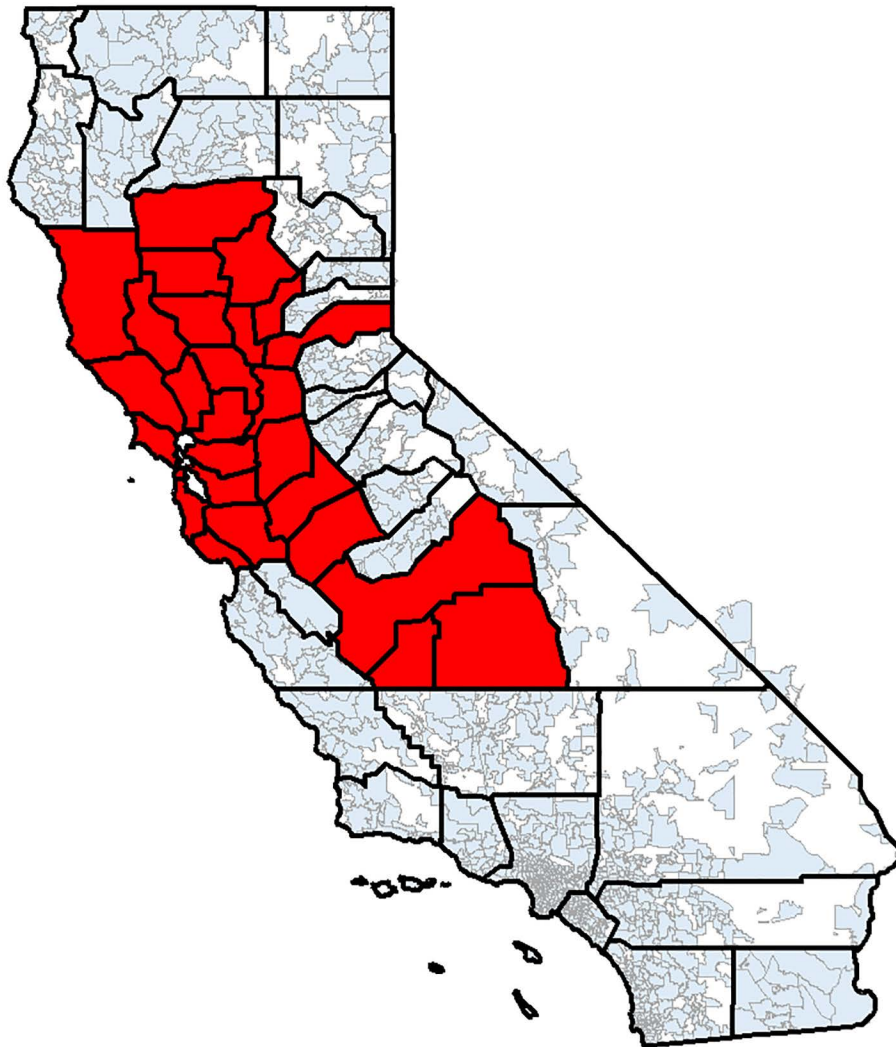


Figure 2. California counties considered exposed to wildfire smoke during the November 2018 wildfires.

the treated units and the obtained synthetic control groups were null or close to zero in the pre-exposure period, and (3) no other shocks coincidentally took place during the wildfire smoke event (i.e., common shock assumption). With these causal identification assumptions being met, we used our estimates to infer the causal effects of the wildfire smoke event on the outcomes of interest. Our main estimand of interest is the ATT.

Stage 2: random-effects meta-regression

Results from the synthetic control analysis for each exposed county were extracted for further analysis. The ATT and standard error for each county were population adjusted for a rate of hospitalizations attributable to wildfire smoke per 10,000 population. Standardized sociodemographic variables were estimated by taking the difference in the county-level measure from the mean across counties and dividing by the interquartile range. A random-effect meta-regression was applied to evaluate the effect modification for each of these variables on the observed effect of wildfire smoke.

Codes for reproducibility and replication purposes are available at the following link: https://github.com/benmarhnia-lab/Wildfires_social_vulnerability.

Results

Descriptive information

Meteorological exposures and hospitalizations were assessed before (13 September–7 November 2018) and during the wildfire smoke exposure (8 November–5 December 2018, see details in Figure S1; <http://links.lww.com/EE/A319>) in exposed and unexposed counties (Table 1). For hospitalization variables, there was a notable increase in mean daily respiratory hospitalizations in both exposed (from 265 to 388) and unexposed counties (from 413 to 512) after the start of the wildfire. Mean daily circulatory hospitalization only slightly increased in both exposed (from 168 to 173) and unexposed counties (from 273 to 282) following the start of the wildfire.

Figure 1 displays the mean smoke exposure for California zip codes during the 2018 wildfires, while Figure 2 displays the California counties that we considered to be exposed to wildfire smoke during the 2018 wildfires for the purposes of this study. Counties that were determined to be exposed are: Alameda, Butte, Colusa, Contra Costa, Fresno, Glenn, Kings, Lake, Marin, Mendocino, Merced, Napa, Placer, Sacramento, San Francisco, San Joaquin, San Mateo, Santa Clara, Santa Cruz, Solano, Sonoma, Stanislaus, Sutter, Tehama, Tulare, Yolo,

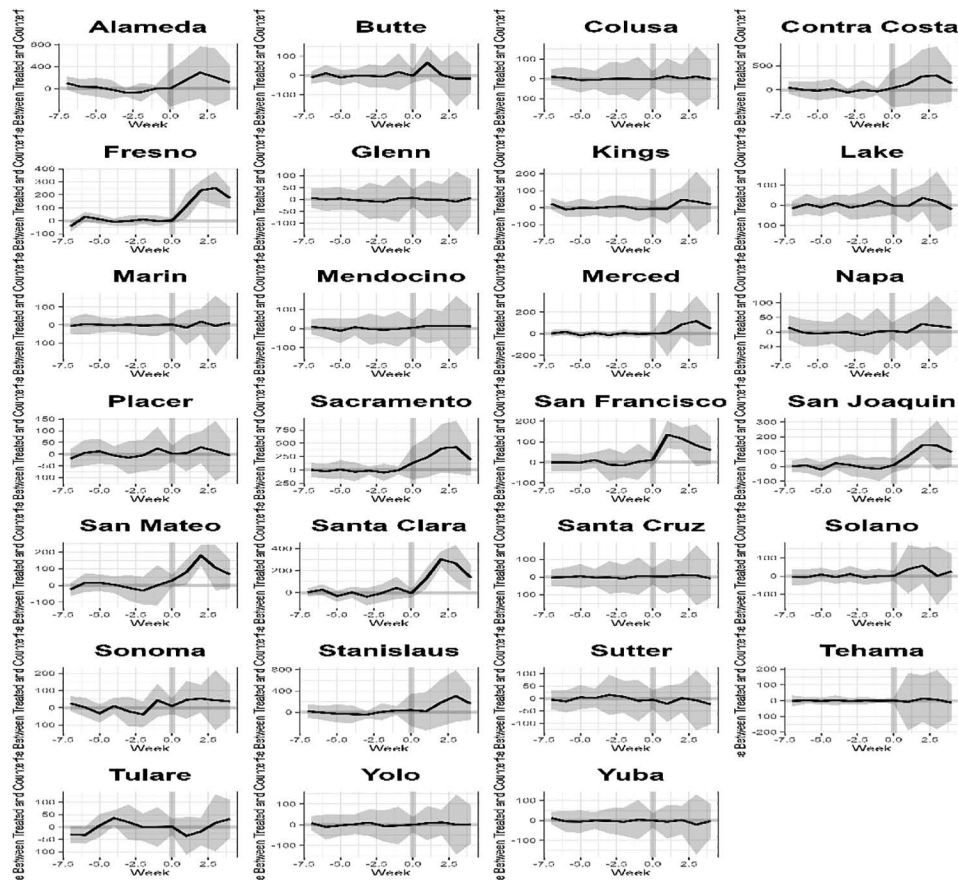


Figure 3. Results of synthetic control analysis of the effect of November 2018 wildfires on respiratory hospitalizations in California for counties exposed to wildfire smoke.

and Yuba (Table S1; <http://links.lww.com/EE/A319>). Figure S2; <http://links.lww.com/EE/A319> shows the average weekly wildfire smoke in exposed and unexposed counties, and Figure S3; <http://links.lww.com/EE/A319> the number of days with wildfire smoke above 10 µg/m³ per week in exposed counties, from 13 September to 5 December 2018.

Sociodemographic mean and standard deviations were calculated for the wildfire smoke-exposed counties (Table S3; <http://links.lww.com/EE/A319>). On average, there was a greater percentage of White people (69.7%) than Asian (10.7%), Black (3.8%), or Hispanic (30.1%) populations among exposed counties. Exposed counties had on average, 50.3% women among their population. The median exposed income in exposed counties was \$68,097 and the median age was 38 years old. Additionally, there was an unemployment rate of 7.3% among the exposed counties. Notably, 28.2% of the exposed counties had an average age of 55 years or older, 15.6% had an average age of 65 years or older, and 1.9% had an average age of 85 years or older. Around 56.6% of the population in exposed counties were, on average, high school graduates or higher.

Main results for stage 1: health effects of wildfire event: findings from a generalized synthetic control analysis

Using a reweighting approach to predict the outcome in the treated unit during the posttreatment period, we were generally able to find good matches for synthetic controls (i.e., difference ~0) in other unexposed California counties. The analysis included 27 exposed and 31 unexposed counties. Overall, we observed an increase in respiratory hospitalizations for most exposed counties when compared with unexposed counties (Figure 3); however, only a few counties showed precise effects

of wildfire smoke. The following exposed counties were found to have significant increases in respiratory hospitalizations: Fresno (ATT of 193.7; 95% confidence interval [CI]: 78.1, 309.2), San Francisco (ATT of 97.9; 95% CI: 11.1, 184.7), San Joaquin (ATT of 113.1; 95% CI: 16.3, 209.9), San Mateo (ATT of 107.9; 95% CI: 5.6, 210.2), and Santa Clara (ATT of 207.9; 95% CI: 110.6, 305.1) (Figure 4, Figure S4; <http://links.lww.com/EE/A319>, and Table S2; <http://links.lww.com/EE/A319>). There was no effect found in circulatory hospitalizations in exposed counties when compared with the synthetic controls (Figure S5; <http://links.lww.com/EE/A319>).

Heterogeneity in health impacts: findings from a random-effect meta-regression

Meta-regression was applied using results from the synthetic control analysis for exposed counties to evaluate the effect modification for each of these county-level socioeconomic variables on the observed effect of 2018 wildfires in California on respiratory hospitalizations (Figure 5). We found no evidence that the county-level sociodemographic variables modified the effects of wildfire smoke on respiratory hospitalizations.

Discussion

This study proposed an analytical framework based on a two-stage GSC method as an alternative to traditional approaches for assessing the heterogeneous health effects of extreme events such as wildfire and exploring their potential drivers. Using the 2018 California wildfire season, one of the deadliest and most destructive wildfires in California’s history, as a case study, we

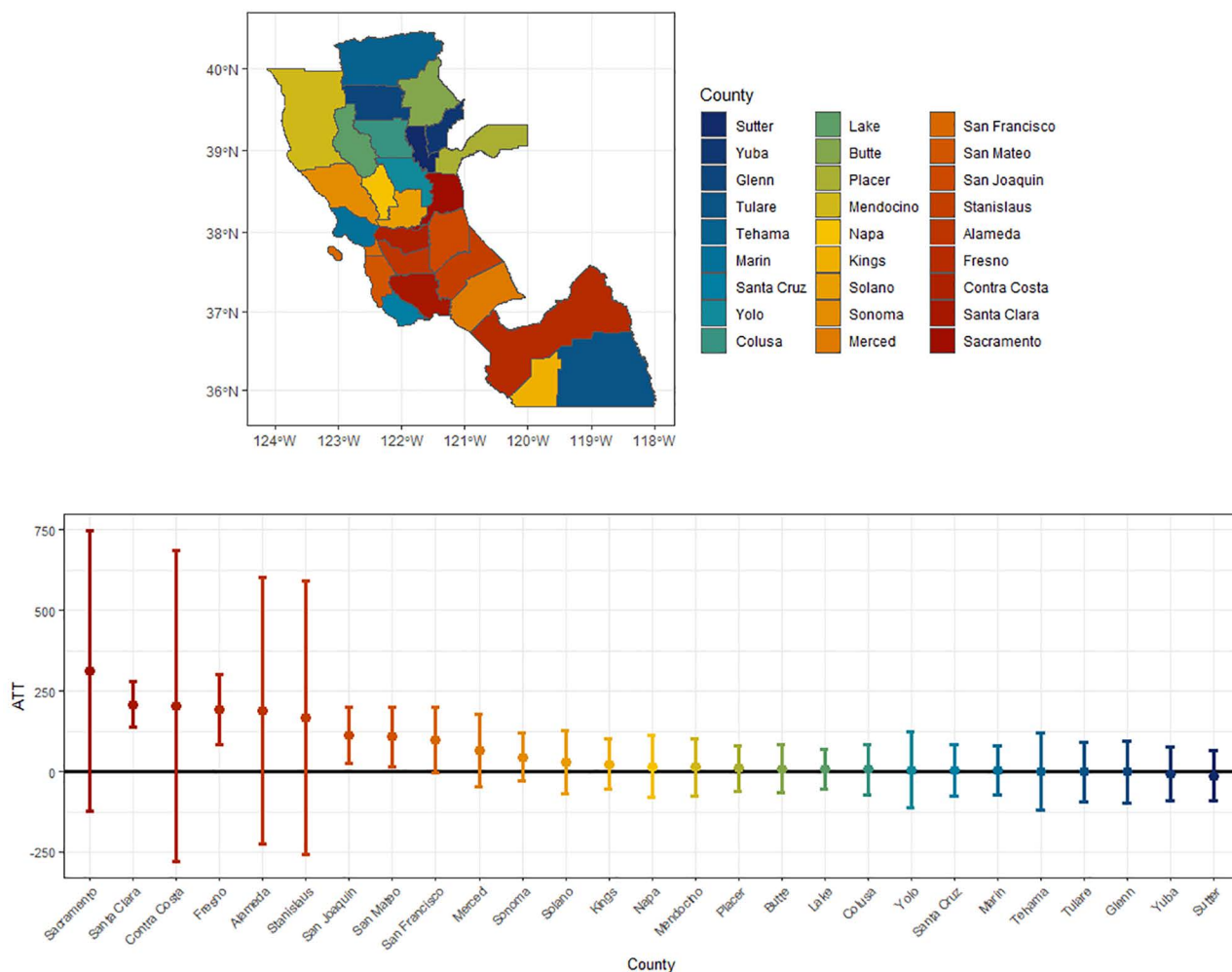


Figure 4. ATT and 95% CI by county for the effect of 2018 wildfires on respiratory hospitalizations.

found an increase in respiratory hospitalizations in most counties that were exposed to wildfire smoke when compared with unexposed counties. In particular, Fresno, San Francisco, San Joaquin, San Mateo, and Santa Clara counties faced significant increases in hospitalizations. No effect of wildfire smoke was observed for circulatory-related hospitalizations. We found no evidence that sociodemographic characteristics at the county level modified the effects of wildfire smoke on respiratory hospitalizations.

Understanding the drivers of the heterogeneous effects of climate-sensitive exposures, such as wildfire smoke events, is important for several reasons. First, documenting these vulnerabilities, as well as resilience factors, is essential to designing adaptation and emergency response strategies that prioritize vulnerable communities and reduce the uneven burden they face.⁴² For instance, in the event of a wildfire where the main vulnerable population is elderly or of low SES with lower-than-average internet accessibility, social media posts would likely not be an appropriate or effective method for disseminating alerts.⁴³ Other vulnerable populations could require communication in languages other than English.^{44,45} Second, understanding the heterogeneous impacts of wildfire events is important for planners to be able to determine how to allocate resources proportionately to expected impacts ahead of or in the aftermath of a disaster.^{46,47} Finally, it also helps us to gain a better understanding of the compounded impacts of wildfires with other concurring risks. We did not aim at comprehensively investigating such mechanisms but rather highlight how the approach we propose can be used in various settings including for studying

the compounded impacts of extreme weather events and infectious diseases.

In this study, the health impacts of major California wildfires in 2018 are investigated using QEM, more specifically GSC. The GSC method is a powerful approach that combines synthetic control techniques with interactive fixed-effect models, as introduced by Xu.³⁷ The GSC approach was found to provide accurate estimates across a range of simulation scenarios compared with more traditional methods such as difference-in-differences and synthetic control methods.⁴⁸ The GSC method proves especially advantageous when applied to the assessment of extreme weather events³⁵ such as wildfires, as such events often exhibit widespread impacts, causing treatment effects to vary significantly across different regions, and frequently coincide with other environmental exposures. Using GSC to estimate the impact of wildfires allows for indirect confounding adjustment and explicit definition of a counterfactual trend and does not require detailed individual-level data. Furthermore, this approach also accommodates multiple exposed units and accounts for both time-varying confounding and heterogeneous treatment effects.

We analyzed potential factors that may drive heterogeneous effects across affected counties by considering a second stage to quantify what modulates the amplitude of the ATT identified in the first stage. This approach can be seen as a type of staggered intervention similar to the approach that has been proposed by Callaway and Sant’Anna⁴⁹ for staggered difference-in-differences. When enough never-treated units (units that are never exposed) are available to build synthetic control groups

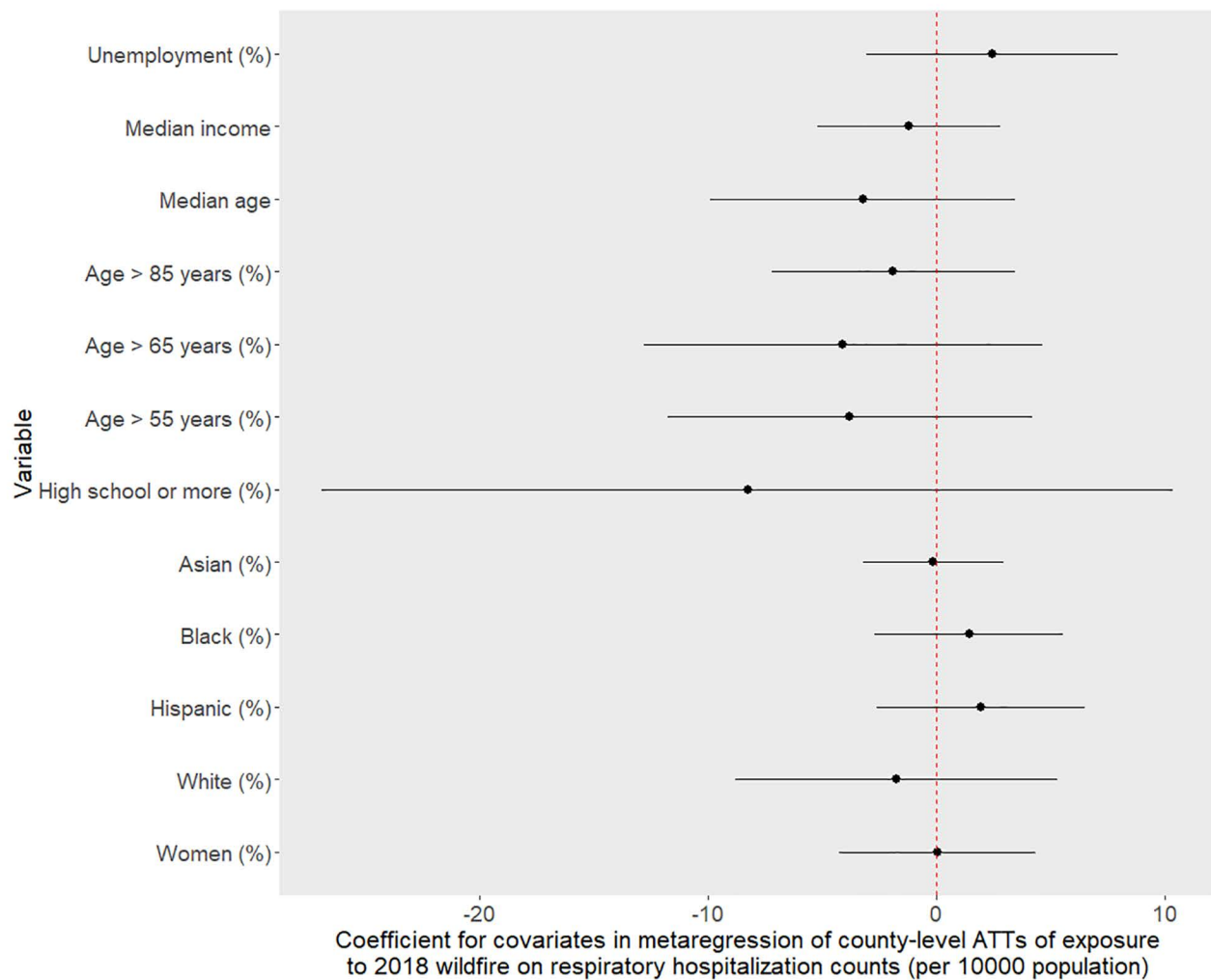


Figure 5. Results of meta-regression of change in effects of wildfire smoke on respiratory hospitalizations for standardized increase in county-level sociodemographic variables during November 2018 wildfires in California.

for each treated unit, such an approach can be implemented. In our example, we capitalized on the spatial variability of the impacts to evaluate effect modification. Yet, this approach could be extended to multiple events or staggered interventions over multiple treated units. For example, wildfires affecting the same area (or different areas) at different times can be a good opportunity to understand if (and why) the health impacts of wildfire smoke vary over time. In such settings, it is necessary to estimate an ATT for each event and for each exposed county. In the second stage (i.e., a random-effect meta-regression), it will be therefore necessary to include a fixed effect at the county level to consider the dependence of the effect estimates within the same area. It is important to note that one potential question of interest can be related to quantifying the differential effects across multiple events and in such a situation, a variable capturing the order of the wildfire smoke event within an area can be included in the meta-regression stage.

In the case study presented in this article, we focused on spatially compounding impacts, but this approach can also be used to explore temporally compounding impacts,⁵⁰ when a succession of hazards leads to differential impacts. Previous studies based on traditional time series modeling have also relied on a similar two-stage approach to explore the drivers of the heterogeneous effects of environmental exposures across space.^{51,52} Our approach is different as we focus on specific events and, besides time-fixed effect modifiers, we can also incorporate

time-varying effect modifiers in the second stage. For example, consider multiple wildfire smoke events (or any other extreme weather events such as extreme heat events) affecting multiple areas, it would be possible to analyze each wildfire smoke event's features (e.g., quantity of wildfire-PM_{2.5}, temperature, concentration of other background pollutants during the event, and infectious disease patterns) that may modulate the effects.

Our findings are consistent with prior research, as we observed respiratory effects associated with exposure to wildfire smoke but found no such association with cardiovascular outcomes. Previous studies have consistently found positive associations between exposure to wildfire smoke and an increase in emergency departments or physician visits for respiratory outcomes, or an exacerbation of asthma and chronic obstructive pulmonary disease.^{10,26,53–55} In contrast, studies focusing on the effects of wildfire smoke on cardiovascular health display a lack of consistent findings, with the majority of studies not identifying any association between wildfire smoke and outcomes related to cardiovascular diseases.¹⁰ A study using generalized estimating equations found that the 2003 Southern California wildfire storm led to a 17% increase in daily respiratory admissions after the fires compared with the prefire period.⁸ Another study, using the GSC approach, found that the 2007 southern California wildfire storm resulted in an 18% increase in respiratory hospitalizations.³⁵ In this case study, we did not identify heterogeneous effects of wildfire smoke. Such findings may

largely be attributed to a lack of statistical power as we assessed effect modification based on county-level vulnerability factors across 27 exposed counties. Nevertheless, our main goal was to illustrate how such a framework can be employed to explore such patterns.

Regarding our causal identification assumptions, we ensured that: (1) geographical units eligible as potential control groups were not exposed to the smoke event; (2) differences in hospital admission incidence between the treated units and the synthetic control groups were negligible or nonexistent during the pre-exposure period, and (3) no other coinciding shocks occurred place during the wildfire smoke event. Overall, we believe these assumptions are met in this case study. We were generally successful in identifying well-matched synthetic controls, with minimal differences (close to zero), in other unexposed counties in California. Moreover, the common shock assumption should be satisfied, ensuring that the observed effects can be attributed solely to that wildfire event (and no other shocks). However, our classification of counties may have led to misclassification of exposure. Counties classified as unexposed may, in reality, have been exposed to low levels of wildfire-PM_{2.5}, as no counties remained completely unaffected by the massive 2018 wildfire event. In addition, it is worth mentioning that some spillover effects may be present as some counties may experience a slight increase in smoke exposure, which can lead to more hospitalizations. In parallel, as we used the place of residence for each hospital admission, it is also possible that some misclassifications may occur as some individuals may not be necessarily admitted in their county of residence.

This study presents other limitations and areas for future development. First, we analyzed the effects of wildfire smoke on health at the county level in order to have sufficient statistical power. We acknowledge that the county level is not the ideal scale for such an analysis as the average treatment effect is averaged across relatively large areas. Assessing the spatial variation in the impact of wildfire smoke exposure within a county could lead to more nuanced results. Moreover, we did not consider spatial dependency between geographical units that could be leveraged in a Bayesian spatial model to improve the statistical precision of the variance and deal with spatial autocorrelation. Combining Bayesian Hierarchical models with GSC methods in such a framework constitutes a promising area for future research. Finally, we did not consider other air pollutants emitted by wildfires (e.g., O₃) or other factors besides wildfire smoke that could lead to increased respiratory hospitalizations. For example, we know that extreme weather events such as heat waves may co-occur with wildfire events and have synergistic health effects,⁵⁶ yet this was not addressed in the present study, which mostly aimed at illustrating an analytical framework.

Conclusion

This study aimed to demonstrate a novel analytical framework, based on QEMs, particularly well suited to assessing the health impacts of extreme weather events and the drivers of their heterogeneous effects. We evaluated the respiratory and circulatory-related hospitalizations associated with an extreme wildfire event at the county level in California, using a two-stage GSC method. We found that the November 2018 wildfires resulted in increased respiratory hospitalizations in most of the exposed California counties with important variability across counties. We explored multiple effect modifiers to explain such variability. This framework can be used in broader settings to understand spatially and temporally compounded health impacts of climate hazards.

Conflicts of interest statement

The authors declare that they have no conflicts of interest with regard to the content of this report.

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