

Advancing Causal Inference in Climate Disaster Epidemiology: Evidence from Wildfires and Power Outages

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ABSTRACT

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As climate change accelerates and reshapes the ways in which our environment affects human health, the frequency and severity of wildfires have been steadily increasing. Unfortunately, climate disasters such as wildfires cannot be fully prevented, so we must turn to mitigation strategies instead. To target such policies and interventions appropriately, we must weigh the full range of impacts of climate disasters and tradeoffs we make with different mitigation strategies — economic and logistical, but also human health and societal. Just as important is understanding the direct health and healthcare utilization effects of a climate disaster as it unfolds, which is critical to mounting a timely, well-resourced response — for example, anticipating surges in emergency department and inpatient care in the days following a wildfire. Often, strategies intended to mitigate the effects of a devastating climate disaster not only have the potential to themselves cause harm, but end up coinciding with the very disaster they were initially intended to prevent. This is often the case with

public safety power shutoffs (PSPS) meant to prevent wildfires. Understanding the health effects in these cases – of the climate disaster itself, its mitigation strategies, and the co-occurrence of the two – as well as developing the methodological tools needed to rigorously study them, is essential.

However, challenges arise in studying health effects of climate disasters. Climate disasters cannot be randomized, there is often no obvious comparison population, and associational studies, while important, are often insufficient to drive policy change. An association alone does not establish that an exposure causes an outcome, and intervening on an exposure that is merely associated with, rather than one that causes, an outcome can result in inefficient resource allocation and limited health improvements. In response, this dissertation applies quasi-experimental, self-controlled study designs – which build a counterfactual from an exposed population’s own data rather than a separate comparison group – to estimate the causal effects of wildfires and PSPS events on healthcare utilization, and translates these methods into open-source, accessible software.

The first aim used a time-stratified case-crossover design to estimate the independent and joint effects of PSPS events and wildfire fine particulate matter ($PM_{2.5}$) on acute healthcare utilization in California from 2013–2019. Leveraging circuit-level outage data and modeled wildfire $PM_{2.5}$ estimates, this analysis found that severe PSPS events were associated with elevated odds of same-day respiratory and chronic obstructive pulmonary disease (COPD)-specific emergency department and hospital encounters, with evidence of multiplicative interaction between PSPS events and wildfire $PM_{2.5}$ for these outcomes. Associations were strongest among individuals with COPD and adults over 65 years.

The second aim used a two-stage interrupted time series (ITS) approach with machine learning to estimate the effects of the January 2025 Los Angeles fires on healthcare utilization among 3.7 million Kaiser Permanente Southern California members. Using National Oceanic and Atmospheric Administration HYSPLIT trajectories and evacuation zone data to separate $PM_{2.5}$ and evacuation exposure, this analysis found that cardiovascular and neuropsychiatric emergency and inpatient visits increased in heavily smoke-exposed areas in the week following ignition, while respiratory visits declined, and overall care-seeking fell in evacuated areas, with greater reduction in care-seeking among those living in the Eaton vs. Palisades evacuation zones.

The third aim generalized the two-stage ITS with machine learning approach into `its2s`, an open-source Python package. `its2s` provides built-in model architectures, configurable defaults, and a reproducible workflow – including versioning, seed management, and parallelization – for constructing counterfactuals in the absence of comparison populations. The utility of the package and its features are showcased in two case studies, one using a simulated policy intervention and another examining excess injury mortality following the 2021 Pacific Northwest heat dome. This package is intended to lower the technical barrier to applying this method broadly across environmental epidemiology and other disciplines.

Together, these three aims demonstrate that self-controlled quasi-experimental designs can generate causal evidence on the health effects of wildfires and power outages even where no randomized trial is possible or a comparison population is available. Wildfires themselves drive substantial cardiorespiratory and neuropsychiatric morbidity, though these effects can diverge by outcome, timing, and exposure pathway – smoke and evacuation do not affect all forms of care-seeking the same way or on the same timeline. PSPS events – despite being designed to prevent wildfires – carry their own distinct health harms when the power goes out, impacts that may be compounded when PSPS events co-occur with wildfires nonetheless. This evidence points to specific, actionable gaps in current mitigation policy – the need to weigh the health harms of PSPS events against the wildfire risk they are designed to prevent (aim 1), the need to target protections toward populations who are most vulnerable (e.g., individuals reliant on electricity-dependent durable medical equipment) (aim 1), and the need to prepare healthcare systems for these shifting cardiorespiratory and neuropsychiatric care needs in the wake of wildfires (aim 2). To do this, we need both the empirical evidence and the methodological tools to target such efforts appropriately (aims 1, 2, and 3). As wildfires, co-occurring power outages, and other climate disasters continue to intensify and expand geographically, this dissertation’s methodological and software contributions provide tools for generating the causal evidence needed to guide policy to protect population health.

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DEDICATION

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CHAPTER 1

INTRODUCTION

1.1 Background: climate change and health.

Climate change is reshaping planetary and human health. Among the most striking displays of this shift is the increasing frequency and severity of climate disasters, particularly wildfires.¹ Across the United States (US) wildfire seasons have lengthened and intensified, and individual fires have grown larger, more frequent, and more widespread.^{2–5} As the wildland-urban interface (WUI) expands across the US, more people than ever are in the path of these intensifying fires.⁶ Looking ahead, wildfire smoke exposure is projected to continue rising, and the associated human impacts to grow substantially in the absence of immediate and considerable mitigation efforts.^{7,8} Together, intensifying fires and a growing exposed population position wildfires as a mounting human health threat.

Wildfire dynamics are especially pronounced in California, where a disproportionate share of the nation's most destructive wildfires has occurred – a trend expected to continue.^{9,10} With 1.5 million new homes built in the WUI since 1990 – making it the fastest-growing WUI in the nation – California now has more than one-third of its households situated in the WUI.¹¹ Against this backdrop, California's large population and regular extreme wildfires place an outsized number of people in a potential wildfire path.

1.1.1 Wildfires and health.

Wildfires affect health through several distinct pathways, of which smoke inhalation is the most studied and understood.¹² Wildfire smoke is a complex mixture of pollutants, including gases, volatile organic compounds (VOCs), and fine particulate matter (PM_{2.5}), and wildfire emissions are also a growing contributor to secondary formation of surface ozone pollution.^{13,14} Of these pollutants, wildfire PM_{2.5} has been the most widely linked to morbidity and mortality.^{15–20} Increasingly, the literature shows that PM_{2.5} from wildfires specifically may be more harmful to respiratory health than PM_{2.5} from other sources, a difference that is hypothesized to be attributed to wildfire smoke's heavy carbon load and associated organic compounds, which appear to trigger stronger oxidative and inflammatory responses in lung tissue.²¹ Mechanistically, wildfire PM_{2.5} triggers systemic

inflammation and oxidative stress, the proposed biological basis for most of these adverse health effects, though much about the underlying mechanisms remains unknown.^{12,22,23} Several epidemiologic studies have linked elevated short-term wildfire PM_{2.5} concentrations to cardiorespiratory-related healthcare utilization,^{16,22,24,25} and a growing body of work has also linked short-term wildfire smoke to neuropsychiatric outcomes – including anxiety, impaired cognition, and dementia – as well as injuries.^{19,26–29} Some studies have also begun to uncover associations between long-term exposure to wildfire smoke and dementia, cancer, and mortality.^{16,30,31}

The health effects of wildfire may also extend beyond those operating via poor air quality and smoke inhalation. Disruption to daily life, evacuation, displacement, destruction of homes and infrastructure, power outages, and the acute stress of a fire disaster are among the other pathways through which wildfires affect health, independent of smoke.^{12,32} Living close to a wildfire burn zone has been associated with increased acute healthcare utilization and motor vehicle crashes.^{33,34} Evacuation, specifically, causes stress, poses physical hazards, and disrupts healthcare access. Accordingly, it has been linked to injuries, the exacerbation of chronic conditions, and worsened mental health.^{12,33,35,36}

1.1.2 Power outages and health.

Wildfires often do not harm health in isolation, and one co-occurring hazard that warrants particular attention is power outages. Power outages adversely affect health independently and compound the effects of wildfires, resulting in a more-than-additive effect on health. During outages, households cannot run systems that regulate indoor air quality or temperature, nor can they operate any electricity-dependent durable medical equipment (eDME, e.g., oxygen equipment). By compromising indoor thermal control, interrupting access to medical facilities, degrading communication means, and failing to power eDME, power outages, in the absence of wildfire co-exposure, have been associated with elevated healthcare utilization for injuries, hypothermia and hyperthermia, cardiorespiratory hospitalizations, and mortality.^{37–42} These risks are amplified for vulnerable populations, particularly those reliant on eDME,⁴³ as most backup batteries last less than 12 hours –

and failure of these devices has been associated with elevated cardiorespiratory healthcare utilization.³⁷

Notably, power outages and wildfires frequently co-occur. Failing electrical infrastructure is itself a leading ignition source for some of the most destructive wildfires – exposing populations to concurrent hazards^{44,45} – and the co-occurrence of outages and climate hazards has risen nationally,⁴⁶ with unequal exposures among vulnerable populations.⁴⁷ While wildfires can trigger power outages by destroying infrastructure, some of the recent co-occurrences are due to the start of planned power outages, or public safety power shutoffs (PSPS). These are proactive utility-initiated de-energizations of power lines enacted in response to elevated wildfire risk or active fires.^{32,48,49} PSPS events are designed to protect against wildfires, but may end up occurring with them. When power outages and wildfires co-occur health impacts may increase substantially, as individuals must cope with both exposures simultaneously, while unable to use air cleaners, eDME, or communication devices.

1.1.3 Inequities in exposure.

The wildfires and power outages – independently and concurrently – do not affect everyone equally. Evidence suggests that both long-term wildfire smoke exposure and power outage exposure persistently cluster in disadvantaged communities.^{18,50,51} The health effects of these exposures are also typically amplified in vulnerable populations who often have higher baseline rates of chronic disease and eDME reliance, inadequate healthcare access, and fewer preparedness resources (e.g., backup power, resources to evacuate).^{37,52} As a result, the populations who are most exposed are often also least prepared, risking a widening of existing disparities.

1.1.4 The health problem.

While efforts to slow or reverse the effects of climate change are widely discussed, climate disasters cannot be fully prevented. As a result, governments and other organizations turn to mitigation

efforts to prepare communities for these events, lessen the impact of disasters, and promptly respond to their effects.⁵³ However, mitigation strategies often incur risks as well. PSPS events illustrate this tension, where the intervention causes one hazard (power outages) in an attempt to prevent a worse one (wildfires).⁴⁹ And, often these two hazards end up co-occurring, leaving communities vulnerable to two, potentially compounding, hazards. Thus, understanding the health effects of wildfire disasters and co-occurring wildfires and power outages is essential to protecting population health as the climate warms – particularly in the most vulnerable communities.

1.2 The epidemiological challenge: exposures, outcomes, and methods.

Studying the ways in which climate disasters affect health, however, presents challenges at all stages of the research process – exposure assessment is difficult due to the sudden and unpredictable nature, the prospectively collected health outcome data is rarely collected before and after the event, and traditional study designs leveraged to establish causation cannot be applied. Next, I describe challenges to epidemiological research of wildfire and similar climate disasters in three domains: exposures, outcomes, and methods.

1.2.1 Exposure data.

By nature, most climate disasters, particularly wildfires, are episodic – they have a rapid onset, a bounded duration, and varying severity both between and within events.^{18,54–56} Further, while early warning systems and projections exist for wildfires, for example, around the world, it remains impossible to predict precisely where and when the next wildfire will ignite, or the next power line will be de-energized. This unforeseeable timing is challenging for community preparedness and resilience as well as for research. It means we cannot design a cohort study or initiate a trial, given the need to know where and when to enroll and follow participants. However, this feature is also an opportunity. Since their timing is exogenous to the underlying health in the affected population, these events can be treated as if occurring at random, lending themselves to study as natural experiments.^{57–61}

Beyond their timing, these exposures are difficult to measure and prone to misclassification.^{18,54,62} Generally, determining the area affected by wildfire PM_{2.5} or the area that lost power is feasible, but ascertaining which individuals were actually exposed or the dose to which they were exposed becomes impossible because we neither observe people's movements or behaviors during the event nor have access to biospecimens or other measures of internal dose.⁵⁴ As a result, wildfire exposure is typically assigned to individuals based on ambient exposure at their residential addresses, which assumes that the person lives at that address, they were home during the event, and outdoor exposure (in the case of wildfire smoke) is a reasonable proxy for an individual's combined indoor/outdoor exposure. Even when these assumptions hold, assigning exposure based on residential address does not capture personal exposure – it remains impossible to know whether someone's windows were open or closed or whether they ran an air filter during a wildfire.²³

Assessing exposure to power outages presents further measurement challenges, too. Unlike wildfire PM_{2.5}, which varies continuously across space, power outages are binary exposures at the household level. A given address either lost power or did not, creating a true exposed and unexposed set of households rather than a continuous surface. However, classifying power outages at the area level typically masks this variation. Absent individual- or household-level data, it is impossible to know the actual outage experience – whether a given household in an “affected” area lost power or not, whether the people captured in the health data were actually home and in an affected household during the outage, whether an affected household had backup power, or whether individuals in an affected household relied on eDME. Without contacting individual households or people, or accessing this kind of individual-level data, it is impossible to know who was actually exposed to this exposure.^{34,37,43,63}

Both wildfire and power outage exposure, while individual-level in nature, must often be assigned at the level of an administrative unit, given health outcome data limitations. Within an administrative unit such as a census tract or county, however, PM_{2.5} concentrations can vary substantially with wind and other meteorological factors, as can the distribution of population and socioeconomic status. Within an administrative unit, actual power outage exposure can also vary household by household, again obscuring an individually-determined exposure beneath spatially aggregated data. This within-unit heterogeneity further complicates accurate exposure assessment.

1.2.2 Outcome data.

As the random, episodic nature of climate disasters generally precludes prospectively identifying and recruiting study participants, climate disaster epidemiology relies largely on observational data.⁵⁷ Researchers leverage electronic health records (EHRs) or administrative claims data that have large sample sizes, are passively collected regardless of a climate disaster, and, in some cases, contain longitudinal patient data.¹⁹ The routine nature of this data collection also means that they exist when and wherever a disaster strikes with relatively complete coverage, high temporal resolution, and no need to enroll participants during a crisis.

These secondary data, however, were not collected for research. Entry into these datasets is neither systematic nor random. Instead, healthcare utilization data represent those who *can* seek care and feel able to do so, or may capture only cases severe enough to warrant a visit. Absence from these datasets is therefore ambiguous. There may be discrepancies between those whom we are able to study and those whom we think (or wish) we are studying.^{64–66}

A person who does not appear in secondary administrative datasets may not have experienced an adverse outcome – or may have sought care outside the catchment of the data source (e.g., a different health system, an out-of-network facility, or a setting not captured by the reporting institutions), may have self-managed the condition without seeking care, or may not have survived to generate a recorded encounter. This concern is compounded in the context of climate disasters, which can prompt population displacement and migration. Climate disasters can result in inaccurate locations or exposure assignment if a patient is either not home during the event – which is often likely – or if patient addresses on file fail to update after a move, and a true outcome may go unrecorded entirely if their care-seeking shifts to facilities outside the source data’s catchment amid the disruption of a disaster, introducing selection bias into the populations captured by secondary healthcare utilization data.^{66,67} Finally, these data typically measure health-related care-seeking, or healthcare utilization, rather than health outcomes directly. Healthcare utilization data capture care-seeking encounters, whereas health outcomes capture the underlying health event itself – which can occur, or not, independent of whether it generates a recorded encounter. Rates of healthcare utilization and health outcomes are inherently linked, but how closely and accurately these constructs vary

together is unknowable.

1.2.3 Epidemiologic methods.

Using these exposure and outcome data sources, we can study the ways in which climate disasters are associated with adverse health outcomes. We are able to compare the rates of health outcomes or healthcare utilization between exposed and unexposed periods or places. A cohort study establishes temporality by following participants over time, but constructing one in precisely the place and period a disaster will strike is nearly impossible.⁵⁹ Typically, a cohort would be established *after* an event, but this eliminates the potential for a self-controlled design and limits potential comparison groups. Even so, when a reasonable comparison group can be identified, these types of associational study can help us understand the ways in which environmental exposures and health vary in tandem and make up the foundation of environmental health research. However, in climate and health research, assembling a comparison population of similar unexposed people is difficult – areas burned by wildfires or that lose power often differ systematically from unaffected areas in ways beyond only exposure status – in geography, climate, and infrastructure – introducing confounding into the selection of a comparison group.^{58,68}

To intervene – to mitigate the *effects* of these exposures – requires understanding causal relationships. An association alone does not necessarily indicate directionality or temporality, so intervening on an exposure that is associated with an outcome, but does not cause it, can result in the intervention having no effect on the outcome of interest.⁶⁶ In order to protect and improve health, we need to establish causal relationships to optimize our mitigation efforts. Establishing causation is also what allows research to guide action – regulatory and policy decisions, such as setting air quality standards, increasingly call for causal evidence rather than association alone. This requires comparing what happened following an exposure with what *would have happened* in the absence of that exposure – or a counterfactual scenario that, while never observed, can be credibly approximated.⁶⁶

Causal inference does not require a randomized trial.^{69,70} While RCTs were long regarded as

a gold standard for constructing a counterfactual – randomizing assignment so that exposed and unexposed groups differ only by chance – many paths lead to causal inference. In many cases, non-RCT inference is better-suited and more appropriate to answer pressing health questions.⁷⁰ For one, a growing body of work indicates that well-designed observational studies also offer a pathway to causal conclusions, often making them complementary to RCTs.⁶⁹ Observational studies are able to draw on a much larger and diverse sample than a trial can enroll, and often can do so in ways that are less ethically and logistically complicated, using methods that are more replicable, and with populations that are more broadly representative.⁶⁹

1.2.4 The methods problem.

This set of exposure assessment, outcome ascertainment, and method selection challenges raises the question – if individual-level exposure cannot be measured, if we do not know who is missing from our health outcome data, if no community can be assigned to be exposed to a climate disaster and thus no community can be assigned as an unexposed comparator, if intentional randomization is impossible – how can we credibly infer causation in environmental epidemiology? This dissertation contributes to the growing body of literature leveraging both novel data sources and methods to begin to answer this fundamental question.

1.3 The methodological challenge.

In the absence of randomization or a clear comparison population, a central methodological problem in climate-disaster epidemiology becomes one of constructing credible counterfactuals from observational data. Causal inference relies on comparing the outcomes that were observed following an exposure with those that would have been expected following the exposure – were the exposure absent.⁶⁶ Yet, we never observe this counterfactual and must instead approximate it.⁶⁶ Under randomization, this is approximated by assignment. In some studies, this is approximated by selecting an unexposed population that is believed to be similar to the exposed on all confounding characteristics. When neither of these are available, the comparison group must be created by the

analytic design itself (Figure 1.1).^{57,59,66}

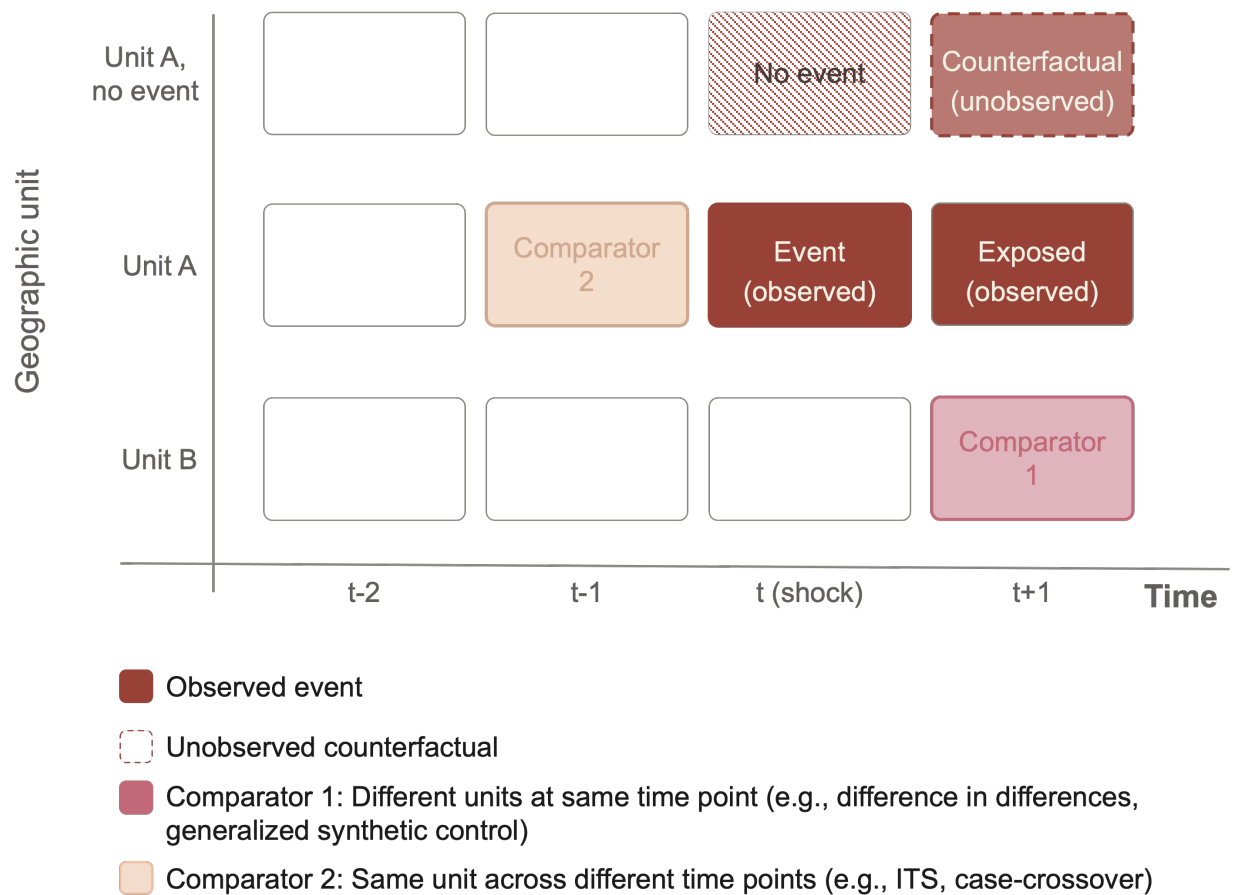


Figure 1.1: Constructing counterfactuals using quasi-experimental methods. A conceptual framework showing two different ways that quasi-experimental designs may leverage natural experiments for causal inference.

1.3.1 Quasi-experimental designs.

Quasi-experimental designs offer one answer to this problem. Gaining traction in environmental epidemiology, they enable the study of natural experiments – settings where some shock, such as a disaster or policy – creates a natural contrast in exposure that, though not randomly assigned, approximates random assignment due to its inherent exogeneity – meaning the timing or occurrence of the shock is unrelated to the factors that would otherwise determine the outcome.^{57,59} Instead of looking to a different population to serve as a comparator, many quasi-experimental designs are self-controlled in that they exploit time within the exposed populations to compare it

to itself. Leaning on the as-if-random timing of these shocks, these methods theoretically recover causal effects in the absence of randomization or distinct comparison populations as they draw on a source of variation that creates a “naturally occurring contrast between a treatment and comparison condition.”⁵⁹

Among the quasi-experimental methods commonly employed in environmental epidemiology, some use a separate comparison group built to have as few confounders as possible with the group under study. Difference-in-differences, generalized synthetic control designs, and the controlled interrupted time series design, for example, build comparators used to evaluate effects.^{58,68,71} This dissertation focuses on another class of quasi-experimental designs that are self-controlled, including the time-stratified case-crossover study and the interrupted time series design. Both of these designs have been successfully used in air pollution and environmental health research.^{19,61,72–75}

The case-crossover and ITS designs share a common logic – each recovers the counterfactual from the exposed unit’s own data across time, rather than from a separate comparison population. They diverge, however, in what each holds fixed and what each allows to vary.

The time-stratified case-crossover design.

In the time-stratified case-crossover design, each individual serves as their own control across time.^{72,76} For each day on which a case occurs, referent days are identified within the same year, month, and matched on day of week, forming one matched stratum per case.⁷³ Exposure on the case (index) day is then compared to exposure on the matched referent days, conditional on the stratum. Because each case serves as its own control, this design inherently controls for time-invariant characteristics; because referent days are drawn from the same individual in the same month and weekday, this matching also holds seasonality, day of week, and slow-moving secular trends constant by design. As such, exposure status is theoretically the only feature that differs between the case day and its referents.⁷⁶ The counterfactual, then, is the case’s own expected outcome across its matched, unexposed referent days.

Using a time-stratified case-crossover design for causal inference comes with important assumptions. First, the exposure must be short-term and the outcome must be acute in its onset – allowing for clear distinctions between index and referent days and ensuring that the effects from the event would not span both the index day and other referent days that month.^{72,75} This design also assumes that the within-stratum distribution of exposure is stationary, such that referent days represent the exposure the case would have experienced had the event been absent.^{73,76} Given these features and assumptions, a time-stratified case-crossover is well-suited to study PSPS events – events that are short-term and abrupt, allowing each PSPS event to be matched to nearby unexposed days that share its seasonal and weekly context, isolating the effect of the event itself.

The interrupted time series design.

In an interrupted time series design, the study population is held fixed and time moves forward across a single, well-defined event. ITS designs model the outcome's pre-event trend and attribute post-event deviations from that trend to the event of interest, making them among the strongest quasi-experimental approaches for evaluating events with clear, abrupt events – particularly valuable when no credibly comparable control units are available.^{61,74,77–79} The design exploits time series data including measurements of an outcome collected both pre- and post-event at regular intervals. The post-event time series represents the observed outcome. ITS designs use the pre-event portion of the time series to estimate the counterfactual by modeling the temporal patterns and projecting them forward to the post-event period. This projected post-event time series becomes the expected post-event time series, or the counterfactual. The fundamental comparison to determine effect is between the observed post-event time series and the counterfactual post-event time series – or what would have been expected had the event not occurred.^{61,77,79}

Importantly, causal inference using an ITS design rests on several assumptions. The first is that the event timing is clearly defined, that no other major event occurs concurrently with the event of interest. Additionally, the design assumes that the pre-event temporal trends would have continued if the event were not to have occurred.⁷⁷

Considering these features and assumptions, the ITS design is well-suited to studying a discrete,

large-scale disasters. In this dissertation, I use the design to study one such disaster – the 2025 Los Angeles wildfires – that interrupted an otherwise stable trajectory of healthcare utilization in a defined population at a very precise, known point in time.

Comparing these two designs.

Both of these quasi-experimental designs compare what happened to what we would have expected to have happened in the absence of a specific, time-bound event. Further, they both generate that comparator using data from the exposed population rather than a separate control group. The two methods differ, though, in what is held fixed. In the time-stratified case-crossover design, each case is effectively fixed and compared only to itself – comparing exposure on an individual's index day with exposure on their matched referent days, so the counterfactual is built from a matched set of unexposed days within the same person. In an interrupted time series, the population is instead held fixed, and we look forward in time, projecting the pre-event trends into the future to estimate the difference in what happened and what would have happened if the pre-event trend were to continue without the interruption of the event.

Thus, while the case-crossover builds a counterfactual by matching unexposed periods for each exposed case-day, the ITS builds a counterfactual by extrapolating a time series – and both compare what happened to what would have happened without the event. Case-crossover designs require unexposed days within the same unit to serve as a referent, making them well-suited to intermittent or recurring exposures, such as PSPS events. Case-crossover designs, however, are poorly suited to study a single, widespread shock that exposes everyone at once, therefore leaving no unexposed period to compare against. On the other hand, ITS designs rely on a stable pre-event trend that can be extrapolated forward to estimate what would have happened in the absence of the event, making them well-suited to discrete, one-time shocks. ITS designs, though, are less well-suited to study recurring exposures, since these repeated interruptions to the time series disrupt the pre-event trend – making it challenging to forecast the counterfactual from it.

1.3.2 Accessibility of these methods.

Successful application of these methods, however, relies on more than the study design being appropriate, the statistical methods being sound, and the assumptions being met. It also relies on researchers having the technical, computational, and methodological expertise to implement the methods.⁸⁰ Successful application often relies on robust and reproducible pipelines with reasonable runtimes and well-documented analytic decisions.^{81,82} This is not always feasible. Many researchers do not have access to a high-performance computing cluster or the time to develop a systematic pipeline that is fully reproducible.^{80,81} Open-source software offers a solution to this barrier. By developing reproducible, accessible, computationally efficient, and user-friendly software, we can provide researchers with tools that facilitate the correct application of these valuable methods, allowing more researchers to apply rigorous study designs to their data without specialized training and infrastructure.^{81,82} In addition to contributing to the methodological literature, this dissertation translates one such method into an accessible, open-source package for researchers to use.

This dissertation fills gaps in the substantive, methodological, and research practice literature surrounding the study of climate and health – contributing to our knowledge of wildfires and closely linked PSPS events, of quasi-experimental methods and causal inference, and of open-source infrastructure for studies of this nature.

1.4 Aim 1: An implementation of the case-crossover study to examine PSPS events, wildfires, and healthcare utilization.

The first aim of this dissertation uses quasi-experimental methods to study the health impacts PSPS events. PSPS events occur when public utility companies proactively de-energize power lines to prevent them from causing or worsening wildfires.⁴⁹ Power outages carry health risks on their own. When they co-occur with the wildfires they are meant to prevent, wildfire smoke can compound existing risks from an electricity outage.⁵¹ It is challenging, however, to study the health

risks associated with PSPS events and co-occurrence with wildfires because these events often suddenly occur, lack clear counterfactuals, and cannot be assigned at random. To tackle these epidemiologic complications, in the first aim of this dissertation, we leverage a self-controlled design, the time-stratified case-crossover study, to assess the impact of PSPS events occurring with and without simultaneous wildfire smoke on acute healthcare utilization in California from 2013 – 2019.

1.5 Aim 2: An implementation of the interrupted time series to examine the health effects of the 2025 LA Fires.

The second aim of this dissertation studies healthcare utilization following the LA Fires. Wildfires affect health through several pathways, most notably smoke exposure and community disruption. The LA Fires, specifically, caused rapidly dispersing PM_{2.5} and widespread evacuation orders, both with the potential to affect health.^{12,19} Studying this single, short climate shock is difficult because no adequate comparator exists – no population was truly comparable to LA at that moment, no other large urban center experienced a major fire during the same period, and complex seasonal trends make the LA population in prior years an unreliable counterfactual. Yet these effects are important to understand, as wildfires in the WUI – and those reaching urban populations – are projected to become increasingly common.⁶ To address this, this aim uses a two-stage ITS design with machine learning to train models on extended pre-event time series of daily cause-specific emergency department and hospitalization utilization at Kaiser Permanente Southern California (KPSC). The approach then uses those models to predict expected post-event trends, which are compared with observed post-event trends. By subtracting the observed utilization from the expected utilization, we can estimate the change in acute healthcare utilization among KPSC members during the week following the January 2025 LA fires' ignition, further distinguishing between wildfire PM_{2.5} and evacuation zone exposure to better understand the underlying mechanisms.

1.6 Aim 3: An open-source Python package for a two-stage interrupted time series approach with machine learning.

The third aim of this dissertation generalizes the two-stage ITS with machine learning approach from the second aim into an open-source Python package, `its2s`. Conducting the second aim effectively required a rigorous, scientifically sound, and reproducible pipeline – which took significant time, technical infrastructure, and computational expertise that research teams may lack. This package, `its2s`, formalizes the approach into a user-friendly implementation that can be used out of the box or configured for advanced users, with customizable model, event, and outcome specifications. The package also supports a reproducible workflow through systematic configuration files, seed management, versioning of inputs and outputs, and parallelization. By lowering the barrier to entry on this method, `its2s` expands the toolkit available for causal inference in natural experiments. In this aim, we describe the methodological foundations and the package’s implementation and demonstrate its use in two case studies.

1.7 Significance and innovation.

Together, the three aims of this dissertation advance quasi-experimental methods for studying the acute health effects of climate disasters, with a focus on two increasingly common hazards – wildfires and power outages. By treating these events as natural experiments, this work leverages two methods – the time-stratified case-crossover and interrupted time series designs – to estimate the effects of these disasters on healthcare utilization. In doing so, this work studies multiple distinct pathways through which these exposures may affect healthcare utilization: wildfire smoke, evacuation, physical proximity to burn zones, and the consequences of the PSPS events intended to prevent ignition. The third aim generalizes the two-stage ITS with machine learning method into an open-source software package, contributing a resource for the continued study of climate disasters and health.

The following chapters will focus on (1) a time-stratified case-crossover analysis of wildfire PM_{2.5}

exposure and PSPS exposure on emergency department and inpatient care encounters across California, (2) a two-stage interrupted time series with machine learning analysis of the 2025 LA fires and healthcare utilization across the emergency department and inpatient settings, and (3) the development of the ITS method into an open-source resource for environmental epidemiologists and other researchers to study the effects of distinct events or interventions in the absence of comparison populations.

CHAPTER 2

AIM 1. CO-EXPOSURE TO PLANNED POWER OUTAGES AND WILDFIRE PM_{2.5} AND ACUTE HEALTHCARE UTILIZATION IN CALIFORNIA

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2.1 Abstract.

Background. To prevent wildfires, electric utilities may preemptively de-energize power lines (public safety power shutoffs [PSPS]).⁸³ These PSPS events may unintentionally harm health, particularly for those with pre-existing conditions like chronic obstructive pulmonary disease (COPD) or who rely on electricity-dependent medical equipment. Health impacts may worsen further if a wildfire occurs despite the power shutoff. To assess the effect of PSPS events, wildfire fine particulate matter (PM_{2.5}) exposure, and their co-occurrence on cause-specific healthcare utilization.

Methods. We identified PSPS events in California from 2013–2019,⁸⁴ categorizing magnitude based on number of people without power by zip code. We leveraged zip code-level average daily wildfire PM_{2.5} estimates⁸⁵ and respiratory, COPD-specific, cardiovascular, and psychiatric emergency department visits and unscheduled hospital admissions among adults aged 20+ from the California Department of Health Care Access and Information.⁸⁶ Using a time-stratified case-crossover design, we estimated the impact of same-day and lagged PSPS events alone, wildfire PM_{2.5} alone, and their co-occurrence on healthcare utilization.

Results. Severe PSPS events were associated with elevated odds of same-day respiratory encounters (OR = 1.06, 95% CI: 1.02, 1.11) and lag₀₋₃ effects were similar. These associations were stronger for COPD. Compared to no PSPS or wildfire exposure, joint PSPS and 10 µg/m³ higher wildfire PM_{2.5} was associated with higher odds of respiratory encounters (1.16 [95% CI: 1.10, 1.22]), with evidence of multiplicative interaction. Associations were null for cardiovascular and psychiatric encounters.

Discussion. PSPS events may increase risk of respiratory events requiring acute care utilization, especially when they co-occur with wildfire PM_{2.5}.

2.2 Introduction.

Climate change has accelerated, driving temperatures higher and increasing variability in precipitation patterns. These higher temperatures and prolonged droughts increase the risk of wildfires. Simultaneously, the number of people living in areas with high wildfire risk has grown.^{6,10} Coupled with fire management practices that yield more available wildfire fuel,¹⁰ these factors have led to increased wildfire frequency, severity, and population exposure in the Western United States.^{6,10,18}

Wildfires impact human health and communities through direct damage and cascading consequences.¹⁸ Residential proximity to wildfires and the fine particulate matter (PM_{2.5}) from wildfire smoke have been associated with adverse cardiorespiratory, neurological, and mental health outcomes.^{16,25,34} Community-level consequences of wildfires include population displacement, damage and destruction of homes and infrastructure, and, power outages, including public safety power shutoffs (PSPS) initiated by utilities to prevent wildfires during periods of high winds and dry conditions.^{32,48}

Alone, power outages are associated with elevated healthcare utilization for injuries, hypothermia, hyperthermia, cardiorespiratory outcomes, and mortality likely due to stress, lack of indoor thermal control, reduced emergency and other communication, interrupted medical care, and loss of power to electricity-dependent durable medical equipment (eDME).^{37–39} When the power goes out, people cannot run air filtration systems, refrigerators, air conditioners, or other electricity-dependent devices (e.g., nebulizer machines, oxygen concentrators).³⁷ This can worsen indoor air quality, threaten indoor climate control, and cause stress that may precipitate adverse health outcomes. At particular risk are those reliant on eDME, as back-up batteries generally last <12 hours.⁴³ Oxygen concentrators, a device commonly used by those with chronic obstructive pulmonary disease (COPD), often have a battery life of 3–4 hours.⁴³ A narrative review found that failure of eDME, such as ventilators or other respiratory devices, was responsible for acute respiratory and cardiovascular visits across several power outage studies.³⁷ Beyond individual households, larger outages disrupt shared community infrastructure – including traffic signals, water and sanitation systems, pharmacies, cooling and warming centers, and healthcare facilities – amplifying the potential for population-level health harm³⁷.

Failing electric infrastructure has caused several of California's most devastating wildfires. Despite PSPS, wildfires can still occur. In fact, the co-occurrence of wildfires with power outages in California increased from 2018–2020.⁴⁶ Utility infrastructure may ignite wildfires when power lines come into contact with trees or dry ground—typically as a result of high winds, such as California's strong Santa Ana and Diablo winds.⁸⁷ Wildfires caused by electrical lines can be among the most destructive,⁸⁸ especially when these electrical lines serve dense population centers.

States have begun to adopt adaptive measures like PSPS to protect public safety from wildfires caused by electric infrastructure. One such measure, implemented in California beginning in 2012 and increasingly in other states, is Public Safety Power Shutoff (PSPS) events.^{49,83} During a PSPS event, electric utilities proactively de-energize power lines to prevent them from causing or worsening wildfires.⁴⁹ No studies have evaluated the healthcare utilization impacts of PSPS events, which can result in large populations losing power for >24 hours. While PSPS events are planned, they may impact health similarly to unplanned outages.

PSPS events may also pose an amplified threat when wildfires still occur despite the shutoff, exposing individuals to the adverse impacts of losing power and wildfire smoke exposure. This may happen if a PSPS event is (1) used to prevent a wildfire from worsening, or (2) initiated to attempt to reduce already high wildfire risk, but a wildfire still occurs nearby. The hazard of co-occurring power outages and high concentrations of PM_{2.5} may have synergistic negative health impacts that exceed the sum of their individual effects.

To our knowledge, no epidemiological studies have evaluated this co-exposure. Certain subpopulations may be more vulnerable due to social and biologic risk factors. For example, those living with COPD, who often rely on oxygen concentrators, may face disproportionate risks during power outages and exceptional risk when wildfire smoke is also present.

This study aimed to assess the impact of PSPS events, wildfire PM_{2.5} exposure, and their co-occurrence on respiratory, COPD, cardiovascular, and psychiatric acute healthcare utilization in California from 2013–2019.

2.3 Methods.

2.3.1 Study population.

In this zip code-level time-stratified case-crossover⁷⁶ study in California, we used data on emergency department visits and unscheduled hospital admissions among adults ≥ 20 years of age from 2013 – 2019 from the California Department of Health Care Access and Information (HCAI),⁸⁶ across 1,504 California zip codes where we had access to power outage data and at least one healthcare encounter occurred (97% of zip codes) (Figure 2.4). Based on findings in prior power outage and wildfire literature, we studied all-cause respiratory, COPD, cardiovascular, and psychiatric healthcare encounters.^{18,37} This study was approved by the California Health and Human Services Agency’s Committee for the Protection of Human Subjects (project number 2021-116).

2.3.2 Exposures and covariates.

PSPS data.

We measured exposure to PSPS events from 2013–2022 using data from PSE Healthy Energy, which compiled historic PSPS events from three of California’s major energy providers, Pacific Gas and Electric (PG&E), San Diego Gas and Electric (SDG&E), and Southern California Edison (SCE).^{49,83} These three utility companies cover 88% of electrical customers in California^{89,90}.

The PSPS dataset contains circuit-level information for each PSPS event across these three major utilities. A circuit is a network of electrical lines that deliver electricity from a power source to a defined service area of customers. A PSPS event may impact multiple circuits, so each circuit-event had a start time, end time, duration, and number of customers impacted.^{49,83} Utility companies may not de-energize an entire circuit, and a circuit may be energized and de-energized multiple times throughout an event. Because we lacked information on these two characteristics of outages, we assumed that the number of people affected were evenly spread across the impacted circuit and were without power for the full duration of the circuit-event. Given the small geographic area

covered by a circuit, exposure misclassification is likely minimal.

We overlaid these circuit-level data containing the number of customers affected^{49,83} with high-resolution gridded estimates of population from the 2020 census in California⁹¹ to estimate the number of people theoretically served by each circuit. We then determined the number of customers impacted on a circuit and proportionally split them between zip codes. We used this information to derive our exposure of interest, the total number of customers impacted each day of a PSPS event in each zip code (referred to as our absolute metric in this paper). We examined both (1) same-day PSPS event exposure and (2) same-day + prior 3-days (lag₀₋₃, rolling average for days 0-3) PSPS event exposure. We chose this lag period because while most COPD exacerbations occur quickly (same-day), some may be delayed (median of 4 days). For this reason, as well as the long duration of PSPS events, we assessed exposure over a 4-day period⁹².

We classified event severity by the number of customers without power because larger outages affect more people and impose broader disruption on shared community infrastructure, making them more likely to produce population-level health effects³⁷. Based on tertiles of these counts for each of these, we categorized the magnitude of PSPS events at the zip code level for both same-day and lag₀₋₃ exposure as mild, moderate, or severe for each zip code-event (Table 2.1). Most events exceeded a day, and the median duration was 86 hours. The PSPS tertiles for both exposure metrics were calculated at the zip code-event level to equally weight longer and shorter events and base the magnitude of severity on number of customers without power rather than duration. We also expected reduced exposure measurement error when moving from mild to moderate to severe PSPS events, as more people within a specified zip code were truly exposed during severe events.

Exposure window	Metric	Mild	Moderate	Severe
Same-day	Absolute (customers out)	≤ 61	62–593	> 593
Same-day	Relative	≤ 1	2–145	> 145
Lag ₀₋₃	Absolute (customers out)	≤ 45	46–458	> 458
Lag ₀₋₃	Relative	≤ 1	2–139	> 139

Table 2.1: PSPS exposure classification. PSPS exposure zip code-level magnitude classification cutoffs. PSPS, public safety power shutoff

Because of highly variable population counts within zip codes, we also constructed a secondary

metric meant to measure the relative magnitude of severity of the PSPS event (referred to as our relative metric). This metric was computed by multiplying the total number of customers without power by the proportion of customers affected in each zip code (supplemental methods). We again created tertiles of exposure at the zip code-event level (supplemental methods). Our primary analysis focuses on the absolute metric for the simplicity of interpretation.

Finally, in a secondary analysis, we constructed a metric of PSPS duration. To do this, we calculated a lag₀₋₆ day PSPS exposure as the total number of hours without power by zip code in the week prior to the index or referent day.

Wildfire smoke data.

We used daily wildfire PM_{2.5} estimates at the zip code level.⁸⁵ The estimates were modeled using a set of machine learning models with multiple predictor variables, including air quality monitor data, aerosol optical depth, land cover, and meteorological conditions, to produce daily PM_{2.5} concentrations.⁸⁵ Wildfire-specific PM_{2.5} was then calculated by imputing non-wildfire-related PM_{2.5} concentrations using a chained random forest algorithm and taking the difference between these values and modeled PM_{2.5} concentrations. When comparing the observed PM_{2.5} concentrations across all US Environmental Protection Agency Monitoring sites versus modeled PM_{2.5} concentrations, Aguilera et al. reported $R^2 = 0.83$. We used same-day wildfire PM_{2.5} exposure for same-day models, and lag₀₋₃ averaged wildfire PM_{2.5} exposure for lag₀₋₃ models.

Temperature data.

We linked gridded (4km grid) daily maximum temperature data from gridMET extracted at the location of zip code population-weighted centroids to the index or referent day as a confounder.⁹³

2.3.3 Outcomes.

Our outcome data relied on HCAI individual-level emergency department visits and unscheduled (unplanned/emergency) hospital admissions from 2013–2019, which included date of admission, associated diagnoses based on *International Classification of Diseases, Ninth Edition (ICD-9)* and Tenth Edition (*ICD-10*) codes, hospital zip code, and patient's residential zip code. When a patient's zip code was missing, we used the zip code of the hospital ($n = 10,727$ [0.09%] cases).

Using primary diagnosis codes, we identified combined daily counts of emergency department visits and unscheduled hospital admissions for the following causes: all-cause respiratory, COPD, cardiovascular, and psychiatric (Table 2.3). Diagnostic codes outside the primary position were not used. We chose these cause groups based on previous research of power outages and health.³⁷ We excluded scheduled hospitalizations (e.g., planned/elective admissions) and visits among those 19 years and younger. As such, our analysis includes emergency department visits without hospitalization and acute hospital admissions, the latter typically originating in the emergency department. We refer to emergency department visits and hospital admissions as encounters for ease of reading throughout this paper.

2.3.4 Statistical analysis.

This study examined the association between PSPS events alone, same-day and lag₀₋₃ wildfire PM_{2.5} alone, and their joint impacts on all-cause respiratory, COPD, cardiovascular, and psychiatric emergency department encounters and hospitalizations. We assessed same-day and lag₀₋₃ exposures. Patient index and referent days in this case-crossover study were linked to exposure data using zip code and date. The date of emergency department visit or hospital admission was considered the index day. We selected referent days for every index day by matching on zip code, day of week, month, and year. In other words, if an index encounter occurred on a Monday in January 2015, all other Mondays in January 2015 *except* for the day of the hospital encounter, were considered referent days.

The outcome was whether a case (ED visit or hospitalization) occurred for an individual on that day. For each day with at least one case (index day), we identified matched referent days within the same calendar month (all same weekdays) and created one matched stratum for each case. We then compared PSPS exposure on index days versus on referent days within the zip code where the individual with the case lived using conditional logistic regression while accounting for the matched strata. Each individual served as their own control across time.

Case-crossover studies are commonly used to evaluate short-term exposures and acute outcomes, as they inherently control for time-invariant confounding factors; the time-stratified referent days control for day-of-week and seasonality.⁷⁶ The primary analysis examined the effects of severe PSPS events using an absolute exposure metric and continuous wildfire PM_{2.5}. Secondary analyses examined mild and moderate PSPS events, a relative PSPS exposure metric, and continuous wildfire PM_{2.5}. Because PSPS events typically last more than 24 hours, we performed this analysis between both same-day and lag₀₋₃ PSPS and wildfire PM_{2.5} exposure and healthcare encounters.

Using a single conditional logistic regression model for each health endpoint, we examined the association between (1) a PSPS event alone, (2) wildfire PM_{2.5} alone, and (3) co-occurring PSPS event and wildfire PM_{2.5} exposure and cause-specific emergency department visits and hospital admissions, accounting for the matched strata of index days and referent periods (more details and equation in supplemental methods). Each model included PSPS event exposure, wildfire PM_{2.5} exposure modeled using a linear term per 10 µg/m³, an interaction term between PSPS event and wildfire PM_{2.5} exposure to assess multiplicative interaction, and a natural cubic spline with three degrees of freedom on same-day maximum temperature (selected based on best model fit to account for the potential nonlinear relationship between temperature and health outcomes) (supplement). We assessed co-exposure in two ways: (1) multiplicative scale interaction effect - the deviation from the expected combined effects of PSPS and wildfire PM_{2.5} on a multiplicative scale; and (2) joint effect - total risk of both hazards when they co-occurred (supplement). In secondary analyses, we ran all models for three separate age groupings: (1) all ages over 20 years, (2) 20-64 years old, and (3) 65+ years old.

To account for the possibility that longer PSPS events may have greater health impacts, in our

secondary analysis, we ran a model with a linear term for total number of hours without power in the prior week (lag_{0-6}) as our main PSPS effect. We accordingly parameterized wildfire $\text{PM}_{2.5}$ as a lag_{0-6} day average for consistency. All modeling methods were otherwise the same.

R version 4.4.2 and Python version 3.13.0 were used for all analyses. Code is available on GitHub.

2.4 Results.

2.4.1 Health data description.

This study included emergency department visits and unplanned hospital admissions from 2013–2019 among California residents ≥ 20 years old (Tables 2.2 and 2.4). We studied four endpoints: respiratory encounters ($n=6,682,821$), COPD encounters ($n=516,427$), cardiovascular encounters ($n=2,913,338$), and psychiatric encounters ($n=1,943,709$). Overall, 68.70% of encounters were emergency department visits, while 31.30% were unplanned hospital admissions (Table 2.2).

	All-cause respiratory <i>n (%)</i>	COPD <i>n (%)</i>	Cardiovascular <i>n (%)</i>	Psychiatric <i>n (%)</i>
Emergency department visit	5,599,535 (83.8%)	303,988 (58.9%)	1,306,387 (44.8%)	1,071,198 (55.1%)
Hospital admission	1,083,286 (16.2%)	212,439 (41.1%)	1,606,951 (55.2%)	872,511 (44.9%)

Table 2.2: Emergency department and unplanned hospitalization counts. Emergency department visits (without hospitalization) or unplanned hospital admissions by type of encounter from California Department of Health Care Access and Information from 2013–2019. COPD, chronic obstructive pulmonary disease

During the 7-year study period, there were 11,293 zip code-days with PSPS events (Figure 2.1), and most were classified as 'severe'. Overall, 876 of the 1,721 zip codes in California experienced at least one PSPS event in the study period (Figure 2.4). Most PSPS events occurred in the summer and fall (Figure 2.5).

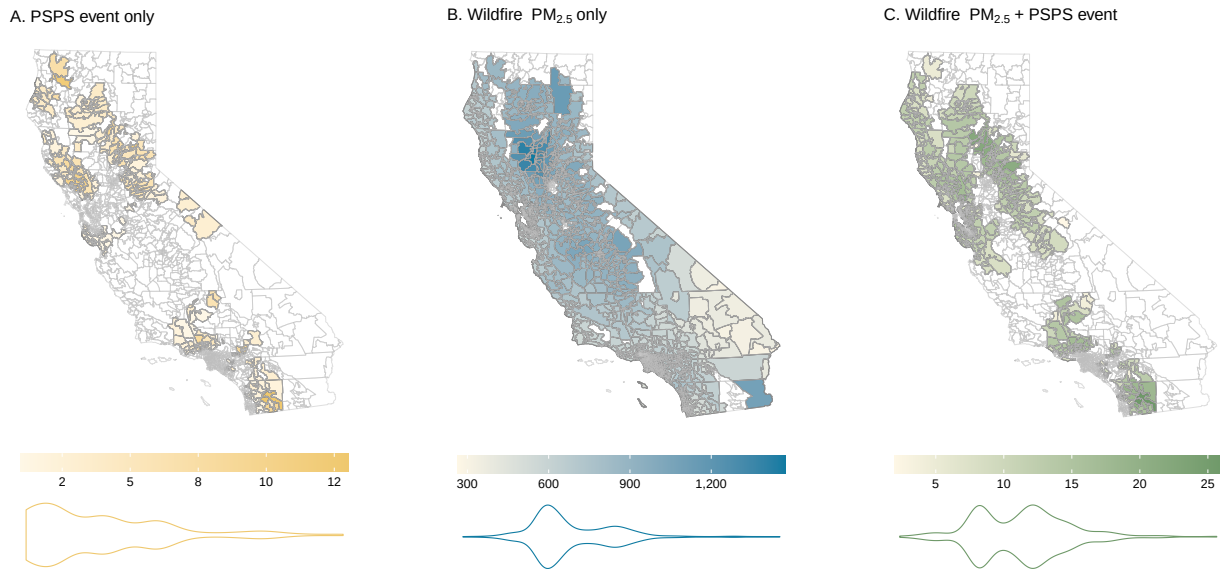


Figure 2.1: Exposure assessment for PSPS events and wildfire $PM_{2.5}$. Number of days with (A) PSPS events alone, (B) wildfire $PM_{2.5}$ alone, and (C) joint PSPS–wildfire $PM_{2.5}$ exposure from 2013 – 2019 by California zip code. These maps are mutually exclusive, meaning that the left panel shows number of days with *only* PSPS events, the middle panel shows number of days with *only* wildfire $PM_{2.5}$, and the right panel shows days when joint exposure occurred. Zip-days were defined as having wildfire $PM_{2.5}$ when wildfire $PM_{2.5}$ was > 0 . This study included zip codes served by the three major energy providers in California – PG&E, SDG&E, and SCE⁴⁹ comprising approximately 75% of California electrical customers. PSPS, public safety power shutoff

We examined our secondary exposure, wildfire $PM_{2.5}$, independent from and concurrent with PSPS events. Among index days, the mean wildfire $PM_{2.5}$ during a severe PSPS event was $3.30\mu g/m^3$, while the mean wildfire $PM_{2.5}$ on non-PSPS days was $0.50\mu g/m^3$. Among referent days, the mean wildfire $PM_{2.5}$ during a severe PSPS event was $3.06\mu g/m^3$, while the mean wildfire $PM_{2.5}$ on non-PSPS days was $0.50\mu g/m^3$. The average wildfire $PM_{2.5}$ concentration during index days among all four outcome categories was generally similar (Figure 2.3; Table 2.5). There were 1,229,438 (27%) zip code-days where there was any wildfire $PM_{2.5}$ from 2013 – 2019 and 7,656 zip code-days with any wildfire $PM_{2.5}$ and a PSPS event (Figure 2.1).

We identified 8,237 respiratory, 965 COPD, 5,304 cardiovascular, 2,276 psychiatric index days exposed to a same-day PSPS event (mild, moderate, or severe) (Table 2.5, Figure 2.3; lagged

values in Table 2.6).

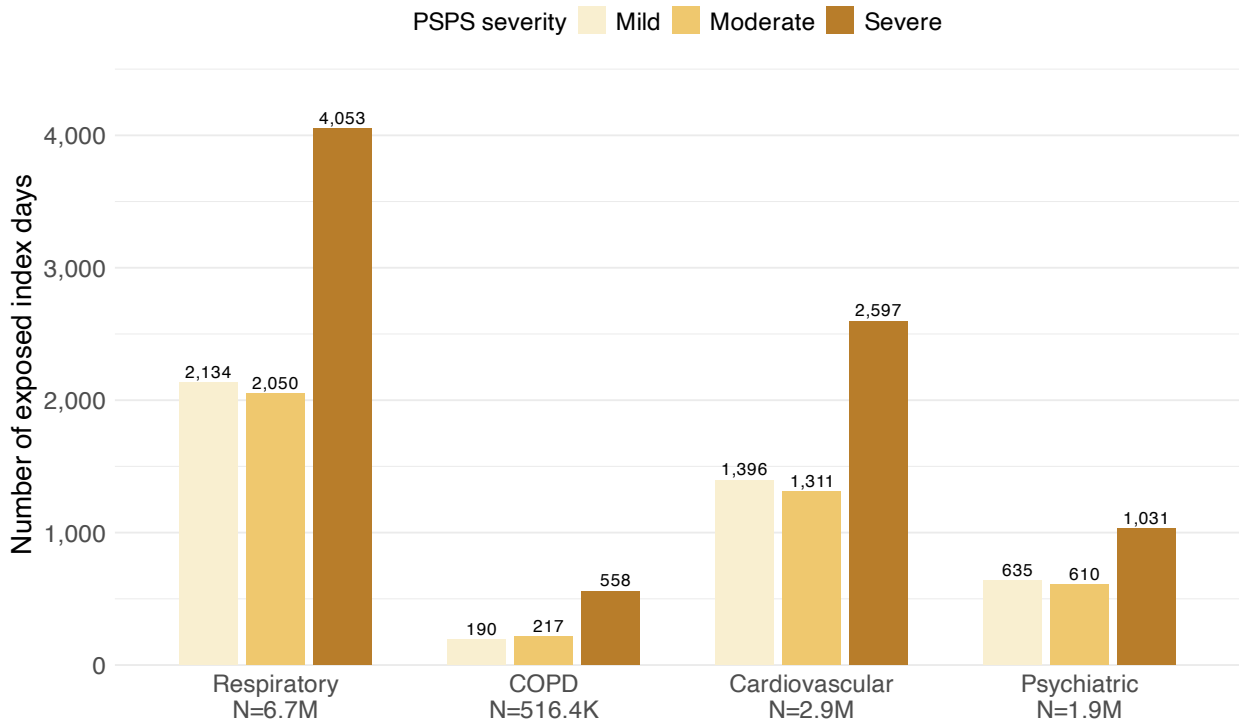


Figure 2.2: Index days by same-day exposure status. Index days were days when a health-care encounter for all-cause respiratory, COPD, cardiovascular, or psychiatric endpoints occurred. Wildfire PM_{2.5} exposure represents the mean wildfire PM_{2.5} concentration on that day. PSPS event magnitude (mild/moderate/severe) was classified using tertiles. PSPS events were classified as mild for those affecting ≤ 61 people, moderate for those with > 61 and ≤ 593 customers without power, and severe for those with > 468 customers without power. COPD, chronic obstructive pulmonary disease; PSPS, public safety power shutoff

2.4.2 Respiratory morbidity.

We found that days with severe magnitude PSPS events and no wildfire smoke were associated with an elevated same-day odds of a respiratory emergency department visit or hospital admission (absolute: OR = 1.06, 95% CI: 1.02, 1.11) (Figure 2.2). Respiratory emergency department visits or hospital admissions were not elevated following lag₀₋₃ PSPS exposure.

A 10 µg/m³ increase in same-day and lag₀₋₃ average wildfire PM_{2.5}, in the absence of PSPS events, were each associated with higher odds of a respiratory emergency department visit or hospital admission (same-day: OR = 1.01 [95% CI: 1.01, 1.01], lag₀₋₃: OR = 1.02 [95% CI: 1.01, 1.02])

(Figure 2.2).

Considering the joint effects, compared to no PSPS event and no wildfire PM_{2.5} exposure, we estimated that same-day severe PSPS event co-occurring with 10 µg/m³ higher wildfire PM_{2.5} was associated with higher odds of a respiratory emergency department visit or hospital admission (1.16 [95% CI: 1.10, 1.22]) (Figure 2.2). We found evidence of multiplicative interaction between severe PSPS events and wildfire PM_{2.5} on respiratory emergency department visits or hospital admissions (1.08 [95% CI: 1.02, 1.14]) (Figure 2.2). Results were similar for lag₀₋₃ exposures, where we detected evidence of multiplicative interaction between severe PSPS events and wildfire PM_{2.5} on respiratory emergency department visits or hospital admissions (1.12 [95% CI: 1.04, 1.20]) (Figure 2.2).

When we isolated COPD encounters, we observed stronger PSPS associations. We estimated that those exposed to a same-day severe magnitude PSPS event had 1.29 (95% CI: 1.15, 1.44) times higher odds of a COPD-related emergency department visit or hospital admission (Figure 2.2). Lagged effects were similar, but smaller in magnitude (1.14 [95% CI: 1.02, 1.27]).

For COPD encounters alone, compared to those exposed to neither a magnitude PSPS event nor wildfire PM_{2.5}, exposure to co-occurring severe PSPS event and 10 µg/m³ higher wildfire PM_{2.5} was associated with higher odds of emergency department visits or hospital admissions (same-day OR = 1.37, 95% CI: 1.19, 1.58; lag₀₋₃ day OR = 1.36, 95% CI: 1.15, 1.60 Figure 2.2). There was potential evidence of multiplicative interaction between severe PSPS events and wildfire PM_{2.5} exposure that was more apparent for lag₀₋₃ exposures (1.18 [95% CI: 0.98, 1.41]).

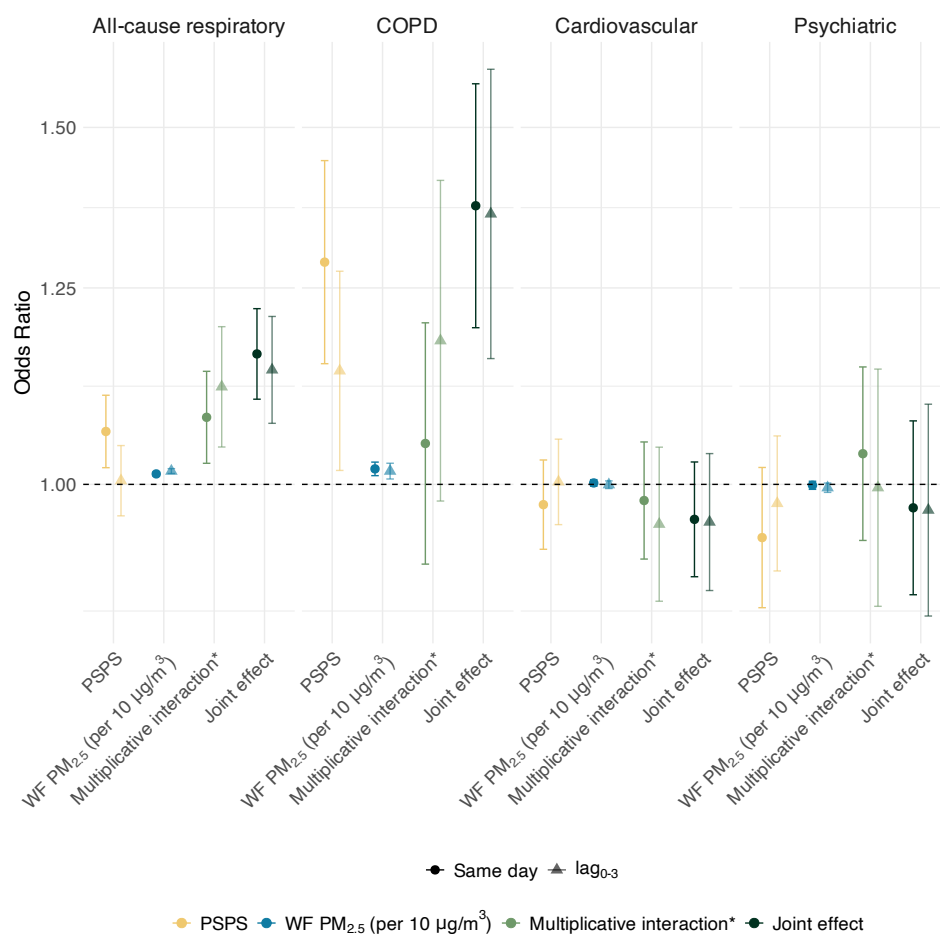


Figure 2.3: Association between severe PSPS events and emergency department visits and hospital admissions. Odds ratios and 95% confidence intervals for the association between zip code-level severe PSPS events and all-cause respiratory-, COPD-, cardiovascular-, and psychiatric-related emergency department visits and hospital admissions in California from 2013 – 2019. Estimates are from separate conditional logistic regression models for each outcome. All models include PSPS event exposure, wildfire PM_{2.5} exposure, an interaction term between PSPS event and wildfire PM_{2.5} exposure, and a spline on mean daily temperature. Exposures are parameterized as same-day or lag₀₋₃, with exposures averaged over lag₀₋₃. COPD, chronic obstructive pulmonary disease; PSPS, public safety power shutoff *Note: The estimate for the interaction effect represents the additional multiplicative effect of joint exposure to wildfire PM_{2.5} and PSPS event on the outcome of interest. It should not be interpreted as an odds ratio in isolation, but is rather a ratio of odds ratios.

Respiratory main effects were consistent across all age strata, however, evidence of multiplicative interaction was present for those ages 20-64 years, but not in older adults (Figures 2.6, 2.8, 2.10). When isolating COPD, the effect of severe PSPS event, as well as the joint effects of severe PSPS event and wildfire PM_{2.5}, were stronger in adults ages 65 years and older (Figures 2.6, 2.8, 2.10).

2.4.3 Cardiovascular morbidity and psychiatric disorders.

We did not observe an association between same-day or lag₀₋₃ mild, moderate, or severe magnitude PSPS events alone, wildfire PM_{2.5} exposure alone, or co-occurring PSPS events and wildfire PM_{2.5} exposure and cardiovascular-related or psychiatric disorder-related emergency department visits or hospitalizations (Figures 2.2 and 2.4). This was consistent in age-stratified models as well (Figures 2.6, 2.8, and 2.10).

2.4.4 Secondary analysis.

In a secondary analysis, we assessed a relative metric of exposure to severe PSPS events (Tables 2.5 and 2.6), and results were similar to those using the absolute exposure metric (Figures 2.7, 2.9, and 2.11). We also examined a relative metric for mild and moderate magnitude PSPS events, and neither they nor their interaction with wildfire PM_{2.5} exposure were associated with any type of emergency department visit or hospital admission (Figures 2.7, 2.9, and 2.11)).

In a secondary analysis using a lag 0-6 day PSPS duration metric, we did not observe an association between PSPS duration and any healthcare encounters. We found modest evidence of multiplicative interaction between 8-hour longer PSPS duration and wildfire PM_{2.5} for respiratory- and COPD-related encounters for those under 65 years of age (respiratory OR = 1.01, 95% CI: [1.00, 1.01]; COPD OR = 1.01, 95% CI: [1.00, 1.03]) (Figure 2.12). These results were null for older adults (Figure 2.12).

2.4.5 Sensitivity analysis.

In a sensitivity analysis where PSPS exposure was parameterized as a continuous measure of total customers impacted, we found that for each additional 1,000 customers without power during a PSPS event, odds of all-cause respiratory emergency department visits or hospital admissions increased (same-day: OR = 1.02 [95% CI: 1.01, 1.02], lag₀₋₃: OR = 1.01 [95% CI: 1.00, 1.01])

(Figure 2.13). When we isolated COPD encounters, as in primary analyses, associations were stronger (same-day: OR = 1.06 [95% CI: 1.04, 1.07], lag₀₋₃: OR = 1.02 [95% CI: 1.00, 1.05]) (Figure 2.13). Consistent with primary analyses, associations for continuous PSPS event exposure were null for cardiovascular- and psychiatric-related emergency department visits or hospital admissions.

2.5 Discussion.

As California's wildfire frequency and severity have increased, electric utilities have initiated more preemptive power shutoffs (PSPS events) to reduce fire risk and spread.⁵³ In California from 2013–2019, we found severe magnitude PSPS events were associated with same-day all-cause respiratory and COPD-specific, but not cardiovascular or psychiatric, emergency department visits and hospital admissions. Wildfire PM_{2.5} exposure alone was also only associated with same-day all-cause respiratory and COPD-specific encounters. The association between PSPS events and respiratory endpoints was stronger in the presence of wildfire PM_{2.5} exposure, especially for COPD.

While both power outages and wildfire smoke are associated with adverse health outcomes, their joint effects are understudied, despite a rise in co-occurrence⁴⁶ and potential for more than additive health effects. Several studies found that power outages appear to amplify the health effects of co-occurring extreme heat, storms, wind events, and floods.^{39,41,94–96} We found evidence of multiplicative interaction between PSPS events and wildfire PM_{2.5} on respiratory healthcare utilization, particularly for COPD. The higher joint effect for COPD was driven by a stronger relationship between PSPS events and COPD encounters than all-cause respiratory encounters. The multiplicative interaction was of similar magnitude for COPD and all-cause respiratory encounters. These findings suggest that climate-driven hazards may be risk multipliers for power outage events.

Limited large-scale epidemiological studies have evaluated the relationship between any type of power outage and health.^{37–39,42,43,97} Generally, health risks appear to rise moderately following power outages, with some evidence that the highest risk is concentrated among those using eDME.^{37–39,42,43,52} In the days following a power outage, most, but not all,^{39,98} studies in New

York State and Florida have found increased risk of emergency department visits or hospitalizations for respiratory illness,^{96,99,100} COPD,^{96,97} cardiovascular disease,¹⁰⁰ food and water-borne disease,¹⁰⁰ injury,³⁸ renal disease,⁹⁹ and carbon monoxide poisoning.³⁸ Our results for severe magnitude PSPS events and respiratory encounters align with most existing literature, as do our null results for cardiovascular disease,^{39,98} suggesting power outages result in acute respiratory, more often than cardiovascular, disease. We found no association with psychiatric encounters, despite participants in two qualitative studies reporting increases in worry, anxiety, and stress following a power outage.¹⁰¹ Although people report worry around PSPS events,¹⁰² their symptoms may not rise to a level warranting emergency psychiatric medical care.

The population health literature around PSPS events remains sparse.^{88,102} Motor vehicle crashes appear largely unchanged during these events⁸⁸ but no studies have evaluated other health outcomes. PSPS events differ from other power outages in their widespread and prescribed nature. The California public utilities commission requires utilities to alert customers of PSPS events in advance, potentially preventing adverse health events that may occur during unplanned outages. Because numerous states now initiate PSPS events, future work must evaluate their impacts on health to inform cost-benefit decision making.

Prior studies have found individuals reliant on eDME, older adults, and those with versus without pre-existing conditions are at higher risk following power outage exposure.^{37,41,43,88,100,103} PSPS events likely pose particular danger to COPD patients, given their reliance on eDME, sensitivity to temperature and humidity changes, and frequent comorbidities.³⁷ Our findings are consistent with this; we found the strongest associations between PSPS events and emergency department visits and hospitalizations were for COPD encounters, particularly among older adults. A large portion (10%) of those with COPD rely on long-term oxygen therapy.^{104,105} In New York State, power outages were associated with increased risk of COPD-related hospitalization, and power outages appear to mediate the association between severe weather and COPD healthcare utilization.^{97,106} Because COPD affects an estimated 4.4% of Californians,¹⁰⁷ future studies should focus on this population and protecting their health during PSPS and wildfire smoke events.

Short-term wildfire PM_{2.5} exposure has been associated with increased risk of respiratory hospitalizations and ED visits, but not consistently with cardiovascular encounters.¹⁶ Studies have also identified associations between short-term wildfire PM_{2.5} exposure and COPD hospital encounters.^{17,25,108,109} Results are mixed for mental health-related healthcare utilization, with some evidence of same-day increases.^{24,26,27} Our study generally agrees with this existing literature.

The majority of epidemiological studies on power outages have constructed binary power outage metrics. These metrics defined a power outage as a percentage of individuals without power (e.g., 5%) within a specific geographic unit.^{38,39,96–98,100} Others considered everyone in an affected area as exposed (e.g., New York during the 2003 blackout).^{99,110} One study used outage data at specific skilled nursing facilities.¹¹¹

Our power outage exposure assessment deviated in several key ways from previous studies. First, we evaluated only PSPS events, which are always planned, proactive cuts to power. The decision to initiate a PSPS event reflects balancing of the societal risks stemming from wildfires and the costs of the PSPS event itself.⁵³ Power utility companies are required to inform customers in advance and take precautions to mitigate the impacts of the outage, such as providing access to Community Resource Centers where individuals can charge devices and access WiFi.⁸⁸ Historically, PSPS events last longer than other types of power outages. Importantly, unlike previous studies, our primary exposure metric was based on counts of customers without power, rather than duration. This is because nearly all PSPS events lasted longer than 8 hours, the cutoff generally used in previous health studies.^{38,46} We found that only severe PSPS events, those impacting > 468 customers, were associated with acute healthcare encounters. In a secondary analysis, PSPS duration appeared a less pertinent exposure, as we found null effects nearly universally with a duration-only based exposure, suggesting household count affected is a key health-relevant component of PSPS exposure.

Limitations.

This study had several limitations. The exposure assessment leveraged power utility data at the circuit level, we lacked individual-level exposure data. Despite circuit-level exposure assessment

being a major improvement on power outage exposure assessment, our assumption that customers were evenly distributed across electrical circuits risks introduction of exposure misclassification. To minimize this, future studies should consider linking individual household location information if available. A second limitation of our exposure assessment is that we aggregated circuit-level data to the zip code level, leading to some exposure misclassification. Further, we assigned exposure at the residential zip code-level but could not ensure that an individual was home during a PSPS event. Individuals may relocate to access power during PSPS events, potentially increasing smoke exposure when traveling outdoors. Finally, our null findings for mild and moderate events may reflect greater exposure misclassification in these categories. Because event severity is defined by the number of people experiencing outages, zip codes classified as exposed to mild or moderate events have fewer residents who actually lost power compared to zip codes exposed to severe events⁶². Importantly, we cannot determine whether exposure misclassification was correlated with wildfire smoke levels. Such correlation could arise if, for example, rural areas with larger circuits (and thus greater misclassification) also experienced higher smoke concentrations, though we lack data to assess this possibility. If present, such correlation would not necessarily bias results toward the null.

Second, the average duration of PSPS events spanned multiple days. To account for this, we examined same-day and lag₀₋₃ day exposures. Future studies may wish to consider more varied lagged effects of PSPS events and wildfire PM_{2.5} exposure.

Third, our study period (2013–2019) spanned a time when PSPS events were relatively new and less frequent. Further, in recent years, multiple major California wildfires have been linked to failing utility infrastructure, including the Dixie Fire (2nd largest, caused by PG&E power lines) and the Eaton Fire (5th deadliest, suspected to be caused by SCE equipment), yet neither had PSPS events initiated. This underscores the need for further study of the interplay between wildfire events, PSPS events, and population health.

Fourth, we captured only individuals aged 20 years and older who visited an emergency department or hospital. Individuals who seek healthcare may systematically differ from those who do not.

Outside hospital mortality was also not accounted for. Additionally, PSPS events may delay care-seeking behavior, and while we only assessed same-day visits, future research should consider longer periods. Because effects in children may differ, future studies should include information on their healthcare.

Fifth, our healthcare utilization categories were broad (respiratory, COPD, psychiatric, and cardiovascular). This may explain our null results for psychiatric endpoints. There is wide discrepancy in care-seeking behavior for some psychiatric endpoints, such as depression compared to substance abuse. Further, we grouped emergency department visits with hospital admissions, however the decision to seek care in these settings differs. Patients or families decide to seek care in the case of emergency department encounters, whereas an admitting physician decides to admit a patient. Future studies may wish to disaggregate the types and causes of encounters.

Further, we could not differentiate emergency department and inpatient admission visits due to data limitations, which may have masked different patterns in these two care settings.

Sixth, healthcare utilization may be disrupted by PSPS events. While hospitals have backup generators, they may still be at risk when diesel cannot be refueled, or generators do not supply sufficient power for all hospital operations. Utilities should coordinate more closely with California healthcare systems when deploying PSPS events.¹¹²

Finally, in an observational study, unobserved confounding may remain. Our case-crossover design effectively handled time-invariant confounding, but short-term time-varying confounders beyond daily ambient temperature, which we controlled for, may remain.

Conclusion.

In the US, the prevalence of wildfires and co-occurring power outages is increasing^{46,113}. Since 2022, states other than California have also implemented PSPS events, including Washington, Oregon, Idaho, and Hawaii⁸³ in response to growing wildfire risk. Our study provides the first analysis of these co-occurring hazards related to health events that require acute care utilization. As the US population ages and more individuals rely on eDME, understanding the respiratory health

implications for PSPS events alone and alongside wildfire $PM_{2.5}$ will allow mitigation strategies that reduce rather than elevate risks to human health.

2.6 Supplemental methods.

2.6.1 Circuit-level data description.

The PSPS dataset contains circuit-level information for each PSPS event across California's three major utilities (Pacific Gas and Electric Company [PG&E], San Diego Gas & Electric [SDG&E], and Southern California Edison [SCE]). A circuit is a network of electrical lines that delivers electricity from a power source to a defined service area of customers. A PSPS event may impact multiple circuits, so each circuit-event had a start time, end time, duration, and number of residential and commercial customers impacted. The circuits were provided as geospatial polygons with an 18-meter buffer around the circuit polyline that was approximated to include all customers potentially served by that circuit. The PSPS dataset contained the number of customers affected by each outage along the circuit. The data contained information on both commercial and residential customers.

We overlaid these circuits with high-resolution gridded estimates of population from the 2020 census in California to estimate (1) the number of customers theoretically served by the circuit, and (2) the number of customers affected and the number of people served at the zip code level. In the absence of more detailed information on customer distribution, we assumed an even distribution of customers across the circuit and performed two spatial overlays of the circuits with the gridded population data. The first used the number of customers impacted on a circuit and split them across zip codes proportional to the overlapped area between the zip code and the circuit, to calculate the number of customers impacted during a circuit-event for each zip code. The second used the population pixels that intersected with each circuit to determine the population served by the circuit and split them across zip codes in the same way to calculate the number of customers served by a circuit for each zip code. By summing the corresponding numbers across all PSPS circuit-events by zip code, we calculated the number of customers impacted and the population served on each

zip code for each PSPS event. Notably, the population served (denominator) remained constant from event to event, while the customers impacted (numerator) changed.

This analysis includes approximately 1,500 zip codes, most of which intersect with several circuits (median = 11, mean = 15; 93% intersect ≥ 2 circuits). Additionally, most circuits span multiple zip codes (median = 2; 31% span ≥ 3 zip codes). In areas included in this study, the median zip code population ($\sim 10,700$) is about five times the median circuit population ($\sim 2,000$).

2.6.2 Absolute (primary) and relative (secondary) PSPS exposure metrics.

We derived and included two daily-zip code exposure metrics meant to capture different aspects of PSPS events. The first metric was the total number of customers impacted in each zip code (absolute metric). Because of highly variable population counts within zip codes, we also constructed a secondary relative metric meant to measure the severity of the PSPS event. The secondary metric was computed by multiplying the total number of customers without power (absolute metric) by the proportion of customers affected in each zip code (total number of customers without power divided by total customers served) to generate the relative metric. This metric was meant to capture both the total number of customers out (as represented in the absolute metric) and the how widespread the power outage was in the zip code – as both aspects of the power outage could influence healthcare utilization. This proportion was calculated using the numerator and denominator described in the *Circuit-level data description*. Exposure for both metrics was categorized as no exposure or mild, moderate, or severe exposure based on rounded tertiles of the non-zero exposure values of each metric for each event-zip code. For our primary metric, the magnitude of same-day PSPS events were classified as mild when ≤ 61 customers were without power, moderate when the number of customers without power was < 61 and ≤ 593 , and severe when > 593 customers were without power. For our secondary metric, magnitude for same-day events was again classified as mild (when our relative metric was ≤ 1), moderate ($1 < \text{relative metric} \leq 145$), or severe (when our relative metric was > 145). For our primary metric, the magnitude of lag₀₋₃ PSPS events were classified as mild when ≤ 45 customers were without power, moderate when the number of customers without power was < 45 and ≤ 458 , and severe when > 458 customers

were without power. For our secondary metric, magnitude for lag₀₋₃ events was again classified as mild (when our relative metric was ≤ 1), moderate ($1 < \text{relative metric} \leq 139$), or severe (when our relative metric was > 139). These tertiles were calculated at the event-zip code level to ensure equal weighting of longer and shorter events and retain the basis of the severity evaluation being on number of people rather than duration.

Given the variability in zip code size, these absolute and relative metrics enabled us to measure exposure to PSPS outages, both in terms of the actual number of customers affected (absolute) and in terms of the portion of customers affected (relative). We leveraged the absolute metric for the primary analysis, and used our relative metric for a secondary.

The PSPS dataset included customers rather than individual people impacted. Customers impacted included both commercial and residential customers, meaning businesses and residences (e.g., individual apartments, single-family residences). This means that our primary exposure metric reflected the number of customers affected, not the number of people affected. For our secondary relative metric, the numerator included customers impacted, while the denominator relied on gridded population data representing individual people. This meant we consistently underestimated the proportion of people without power, but we do not expect this to be differential with respect to outcomes.

2.6.3 Model equation.

Regression Equation

$$\log \left(\frac{p_{ij}}{1 - p_{ij}} \right) = \alpha_i + \beta_1 \cdot PSPS_{ij} + \beta_2 \cdot PM_{2.5,ij} + \beta_3 \cdot (PSPS_{ij} \times PM_{2.5,ij}) + f(Temp_{max,ij}) \quad (2.1)$$

where: $p_{ij} = P(Y_{ij} = 1 | X_{ij}, C_{ij})$ for a case ($j = 1$) or a control ($j = 0$) in stratum ij . i represents each stratum and j represents a case or control in that stratum.

Parameter Definitions

- α_i : stratum-specific intercept that accounts for the baseline risk of the health outcome in each stratum, or matched set in this case.
- β_1 : log odds ratio for emergency department visit or hospital admission associated with exposure to a PSPS event (binary indicator), assuming no wildfire PM_{2.5} exposure and adjusted for temperature
- β_2 : log odds ratio for emergency department visit or hospital admission per 10 $\mu\text{g}/\text{m}^3$ higher wildfire PM_{2.5} concentration, assuming no PSPS event exposure and adjusted for temperature
- β_3 : log odds ratio for the multiplicative interaction between PSPS event exposure and wildfire PM_{2.5} (per 10 $\mu\text{g}/\text{m}^3$). This is the additional effect of 10 $\mu\text{g}/\text{m}^3$ higher wildfire PM_{2.5} in the presence of a PSPS event.
- $f(\text{Temp}_{\text{max}})$: natural cubic spline with 3 degrees of freedom for daily maximum temperature.

PSPS event exposure and wildfire PM_{2.5} exposure represent either same-day or lag₀₋₃, for each of the two main analyses – the timing of the two exposures is always parameterized consistently. The joint effect of a PSPS event and 10 $\mu\text{g}/\text{m}^3$ higher PM_{2.5} exposure was calculated as: $\beta_1 + \beta_2 + \beta_3$.

2.6.4 Secondary analysis using outage durations.

While we omitted duration from our primary analysis, longer PSPS events are likely to have greater health impacts. To assess this, we conducted a secondary analysis where we used number of hours without power in the prior week, irrespective of the number of affected households, as our primary PSPS exposure.

To calculate daily PSPS outage duration by zip code, we expanded each PSPS event to hourly intervals based on its start and end times. We rounded the start time down and the end time up to

the nearest hour. We then de-duplicated overlapping hours across events within the same zip code to avoid double-counting hours when multiple PSPS events affected the same zip code during the same hour. Finally, we aggregated the unique outage hours to the daily level in order to generate the number of hours out per zip code-day (maximum 24 hours per day due to no double-counting hours). We then summed the number of hours without power in the week prior to index or referent day and used this as the PSPS exposure in our models.

2.7 Supplemental tables.

Health endpoint	ICD-9 Codes	ICD-10 Codes
Respiratory	460-466, 471, 472, 477, 478, 480-487, 490-496, 511, 513-519, 786	J00-J06, J12-J18, J20-J22, J30, J31, J33, J34, J38, J39, J40-J47, J80-J86, J90-J92, J94, J96-J99, R04-R07, R09
COPD	491-492, 496	J41-44
Cardiovascular	390-398, 401-417, 420-429, 440-449	I00-I02, I05-I16, I20-I28, I30-I5A, I70-I79
Psychiatric	290-293, 295, 296, 298	F06, F10-F16, F18-F21, F23, F25, F28-F33

Table 2.3: International Classification of Disease, Ninth Edition (ICD-9) and Tenth Edition (ICD-10) codes. used in analysis, by medical condition. COPD, chronic obstructive pulmonary disease.

	All-cause respiratory	COPD	Cardiovascular	Psychiatric
Age Group				
20–49 years	2,799,372 (41.9%)	33,415 (6.5%)	434,901 (14.9%)	1,267,283 (65.2%)
50–64 years	1,816,130 (27.2%)	182,937 (35.4%)	827,568 (28.4%)	509,478 (26.2%)
65–79 years	1,307,829 (19.6%)	197,598 (38.3%)	938,150 (32.2%)	139,455 (7.2%)
80 years and older	759,490 (11.4%)	102,477 (19.8%)	712,719 (24.5%)	27,493 (1.4%)
Sex				
Female	3,831,871 (57.3%)	277,053 (53.6%)	1,368,501 (47%)	779,186 (40.1%)
Male	2,850,703 (42.7%)	239,351 (46.3%)	1,544,695 (53%)	1,164,301 (59.9%)
Unknown, missing, or invalid	247 (0%)	23 (0%)	142 (0%)	222 (0%)
Race/Ethnicity				
Non-Hispanic Black	904,853 (13.5%)	75,193 (14.6%)	334,157 (11.5%)	253,437 (13%)
Native Hawaiian or Other Pacific Islander	464,021 (6.9%)	26,358 (5.1%)	262,388 (9%)	81,212 (4.2%)
Non-Hispanic White	2,907,307 (43.5%)	326,264 (63.2%)	1,489,710 (51.1%)	999,038 (51.4%)
Other or Multiracial	251,544 (3.8%)	13,313 (2.6%)	110,041 (3.8%)	77,130 (4%)
Hispanic	2,057,857 (30.8%)	68,556 (13.3%)	679,615 (23.3%)	491,626 (25.3%)
American Indian or Alaska Native	31,678 (0.5%)	2,945 (0.6%)	11,538 (0.4%)	9,865 (0.5%)
Unknown	65,561 (1%)	3,798 (0.7%)	25,889 (0.9%)	31,401 (1.6%)

Table 2.4: Demographic characteristics of emergency department visits or hospitalizations. included in the study in California from 2013–2019. Each observation represents a single visit, so individuals with multiple visits appear multiple times. COPD, chronic obstructive pulmonary disease.

Disease endpoint	Absolute (primary) Index days	Relative (secondary) Index days
All-cause respiratory		
Exposure (PSPS)		
Mild	2,134	2,907
Moderate	2,050	2,429
Severe	4,053	2,901
None	6,674,584	6,674,584
Exposure (wildfire PM_{2.5})		
Mean (SD), µg/m ³		0.47 (4.09)
COPD		
Exposure (PSPS)		
Mild	190	248
Moderate	217	256
Severe	558	461
None	515,462	515,462
Exposure (wildfire PM_{2.5})		
Mean (SD), µg/m ³		0.53 (4.67)
Cardiovascular		
Exposure (PSPS)		
Mild	1,396	1,885
Moderate	1,311	1,582
Severe	2,597	1,837
None	2,908,034	2,908,034
Exposure (wildfire PM_{2.5})		
Mean (SD), µg/m ³		0.48 (3.94)
Psychiatric		
Exposure (PSPS)		
Mild	635	841
Moderate	610	727
Severe	1,031	708
None	1,941,433	1,941,433
Exposure (wildfire PM_{2.5})		
Mean (SD), µg/m ³		0.49 (3.9)

Table 2.5: Index days by same-day exposure status, absolute and relative metrics. Index days by same-day exposure status. Index days are days when a healthcare encounter for all-cause respiratory, COPD, cardiovascular, or psychiatric endpoints occurred. Wildfire PM_{2.5} exposure represents the mean wildfire PM_{2.5} concentration on that day. PSPS event magnitude (mild/moderate/severe) were classified using tertiles for both absolute and relative metrics. For our absolute (primary) metric, mild events were those affecting ≤ 61 people, moderate were those where the number of customers without power was > 61 and ≤ 593 , and severe was defined as events where > 593 customers were without power. For our relative (secondary) metric, magnitude was classified as mild when our relative metric was ≤ 1 , moderate when $1 < \text{relative metric} \leq 145$, or severe when our relative metric was > 145 . COPD, chronic obstructive pulmonary disease; PSPS, public safety power shutoff

Disease endpoint	Absolute (primary) Index days	Relative (secondary) Index days
All-cause respiratory		
Exposure (PSPS)		
Mild	2,434	3,126
Moderate	2,547	3,077
Severe	4,666	3,444
None	6,673,174	6,673,174
Exposure (wildfire PM_{2.5})		
Mean (SD), µg/m ³		0.47 (3.7)
COPD		
Exposure (PSPS)		
Mild	223	273
Moderate	271	337
Severe	617	501
None	515,316	515,316
Exposure (wildfire PM_{2.5})		
Mean (SD), µg/m ³		0.52 (4.13)
Cardiovascular		
Exposure (PSPS)		
Mild	1,604	2,037
Moderate	1,637	2,059
Severe	3,095	2,240
None	2,907,002	2,907,002
Exposure (wildfire PM_{2.5})		
Mean (SD), µg/m ³		0.48 (3.54)
Psychiatric		
Exposure (PSPS)		
Mild	720	933
Moderate	745	900
Severe	1,212	844
None	1,941,032	1,941,032
Exposure (wildfire PM_{2.5})		
Mean (SD), µg/m ³		0.49 (3.51)

Table 2.6: Index days by lag₀₋₃ exposure status, absolute and relative metrics. Index days by lag₀₋₃ day exposure status. Index days are days when a healthcare encounter for all-cause respiratory, COPD, cardiovascular, or psychiatric endpoints occurred. Wildfire PM_{2.5} exposure represents the mean wildfire PM_{2.5} concentration for lag₀₋₃ days. PSPS event magnitude (mild/moderate/severe) were classified using tertiles for both absolute and relative metrics. For our absolute (primary) metric, mild events were those affecting ≤ 45 people, moderate were those where the number of customers without power was > 45 and ≤ 458 , and severe was defined as events where > 458 customers were without power. For our relative (secondary) metric, magnitude was classified as mild when our relative metric was ≤ 1 , moderate when $1 < \text{relative metric} \leq 145$, or severe when our relative metric was > 145 . COPD, chronic obstructive pulmonary disease; PSPS, public safety power shutoff

	Effect estimates, OR (95% CI)			
	PSPS	WF PM _{2.5} (per 10 µg/m ³)	Joint effect	Multiplicative interaction*
All-cause respiratory				
Same day	1.06 (1.02, 1.11)	1.01 (1.01, 1.01)	1.16 (1.10, 1.22)	1.08 (1.02, 1.14)
Lag ₀₋₃	1.00 (0.96, 1.05)	1.02 (1.01, 1.02)	1.14 (1.07, 1.21)	1.12 (1.04, 1.20)
COPD				
Same day	1.29 (1.15, 1.44)	1.02 (1.01, 1.03)	1.37 (1.19, 1.58)	1.05 (0.91, 1.20)
Lag ₀₋₃	1.14 (1.02, 1.27)	1.02 (1.01, 1.02)	1.36 (1.15, 1.60)	1.18 (0.98, 1.41)
Cardiovascular				
Same day	0.98 (0.93, 1.03)	1.00 (1.00, 1.01)	0.96 (0.90, 1.03)	0.98 (0.92, 1.05)
Lag ₀₋₃	1.00 (0.96, 1.05)	1.00 (1.00, 1.00)	0.96 (0.89, 1.04)	0.96 (0.88, 1.04)
Psychiatric				
Same day	0.94 (0.87, 1.02)	1.00 (0.99, 1.00)	0.97 (0.88, 1.07)	1.04 (0.94, 1.14)
Lag ₀₋₃	0.98 (0.91, 1.06)	1.00 (0.99, 1.00)	0.97 (0.86, 1.10)	1.00 (0.87, 1.14)

Table 2.7: Effect estimates for PSPS exposure, wildfire PM_{2.5} exposure, and cause-specific healthcare encounters. Odds ratios and 95% confidence intervals for the association between zip code-level severe PSPS events and all-cause respiratory-, COPD-, cardiovascular-, and psychiatric-related emergency department visits and hospital admissions in California from 2013 – 2019. Estimates are from four separate conditional logistic regression models. All models include PSPS event exposure, lag₀₋₃ day wildfire PM_{2.5} exposure, an interaction term between PSPS event and wildfire PM_{2.5} exposure, and a spline on mean daily temperature. COPD, chronic obstructive pulmonary disease; PSPS, public safety power shutoff **Note: The estimate for the interaction effect represents the additional multiplicative effect of joint exposure to wildfire PM_{2.5} and PSPS event on the outcome of interest. It should not be interpreted as an odds ratio in isolation, but is rather a ratio of odds ratios.*

2.8 Supplemental figures.



Figure 2.4: Zip codes included in this study. Spatial distribution of the 1,504 zip codes in California included in this study. There were 1,504, 1,464, 1,500, 1,501 zip codes included for all-cause respiratory-, COPD-, cardiovascular-, and psychiatric-related emergency department visits and hospital admissions. COPD, chronic obstructive pulmonary disease.

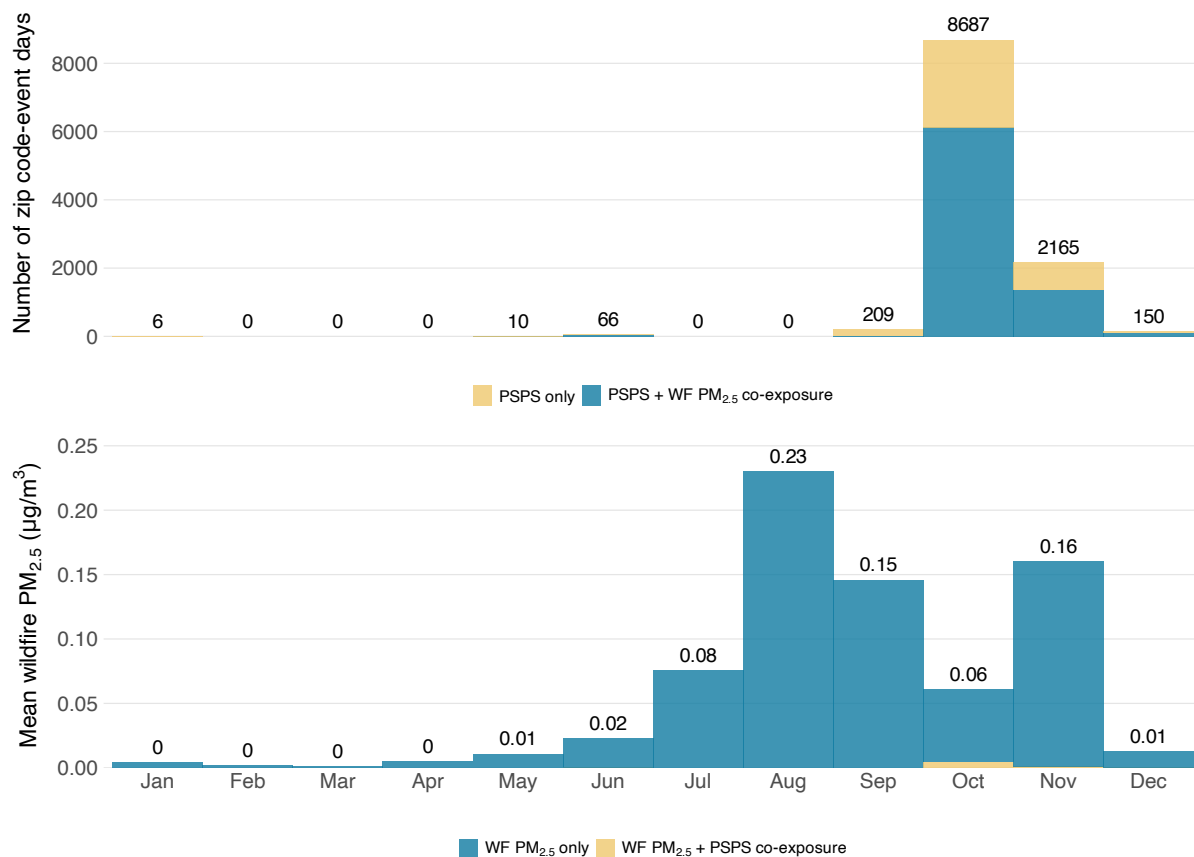


Figure 2.5: Seasonality of PSPS events and wildfire PM_{2.5}, by month, in California during the study period (2013–2019). The number of zip code-event days of PSPS events reflects the sum over the 7-year period, while the mean wildfire PM_{2.5} exposure represents means for each month over the 7-year study period. PSPS, public safety power shutoffs.

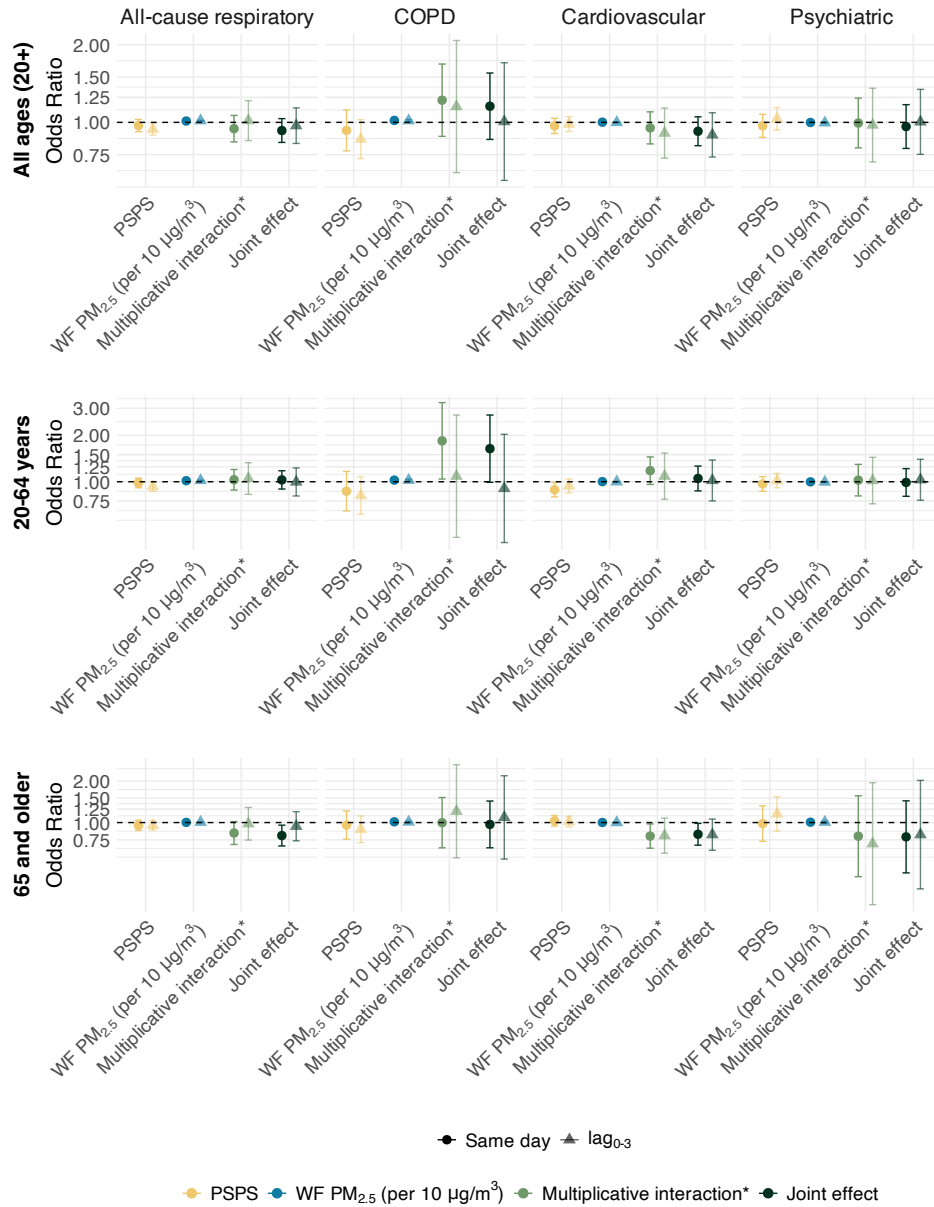


Figure 2.6: Effect estimates for mild PSPS exposure (absolute), wildfire PM_{2.5} exposure, and cause-specific healthcare encounters, by age. Odds ratios and 95% confidence intervals for the association between zip code-level mild PSPS events (absolute metric) and all-cause respiratory-, COPD-, cardiovascular-, and psychiatric-related emergency department visits and hospital admissions in California from 2013–2019 by age group. Estimates are from eight separate conditional logistic regression models, including one for each health endpoint – exposure metric combination. All models include PSPS event exposure, lag₀₋₃ day wildfire PM_{2.5} exposure, an interaction term between PSPS event and wildfire PM_{2.5} exposure, and a spline on mean daily temperature. The absolute metric reflects the number of individuals exposed to a PSPS event, while the relative metric reflects the severity of the event. COPD, chronic obstructive pulmonary disease. **Note: The estimate for the interaction effect represents the additional multiplicative effect of joint exposure to wildfire PM_{2.5} and PSPS event on the outcome of interest. It should not be interpreted as an odds ratio in isolation, but is rather a ratio of odds ratios. PSPS, public safety power shutoff; COPD, chronic obstructive pulmonary disease*

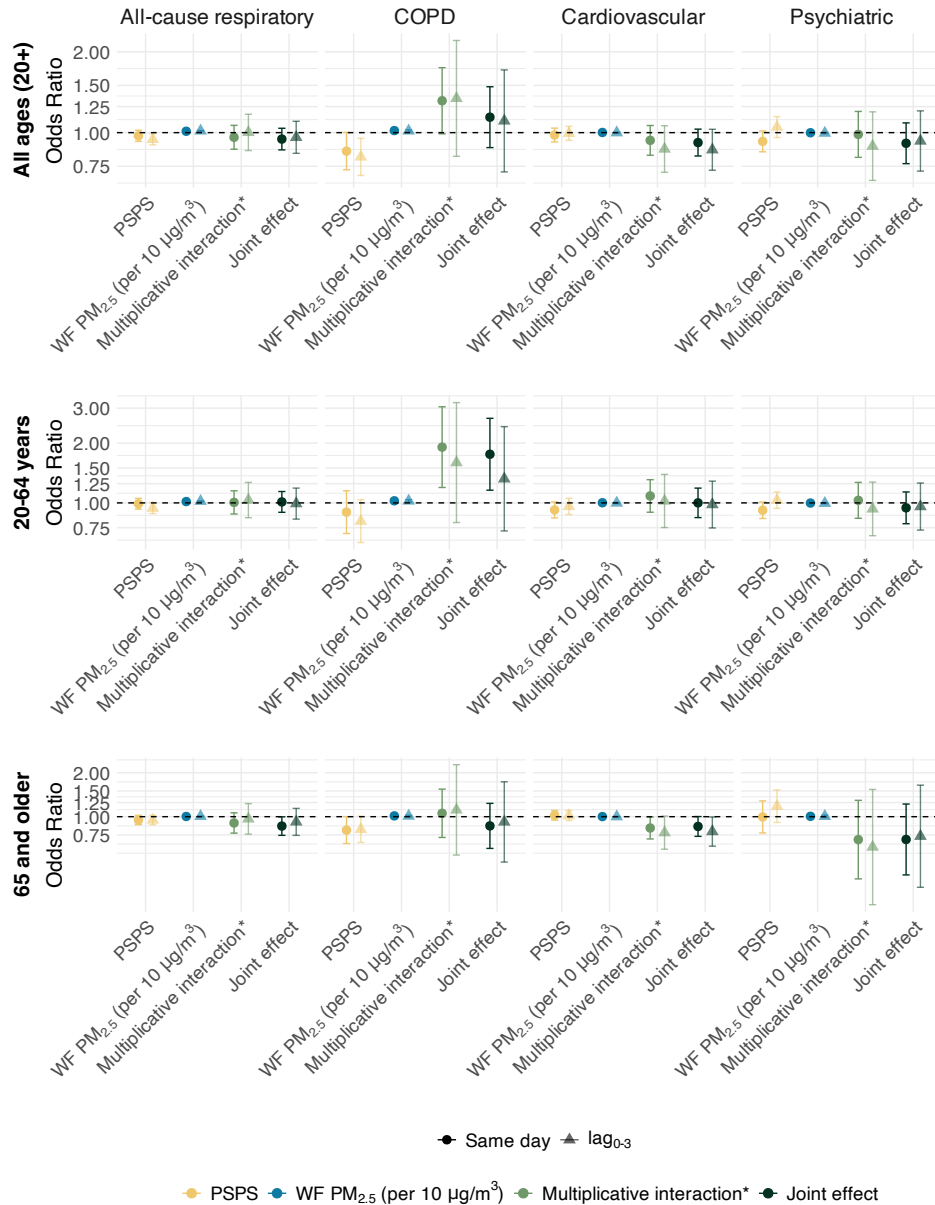


Figure 2.7: Effect estimates for mild PSPS exposure (relative), wildfire PM_{2.5} exposure, and cause-specific healthcare encounters, by age. Odds ratios and 95% confidence intervals for the association between zip code-level mild PSPS events (relative metric) and all-cause respiratory-, COPD-, cardiovascular-, and psychiatric-related emergency department visits and hospital admissions in California from 2013–2019 by age group. Estimates are from eight separate conditional logistic regression models, including one for each health endpoint – exposure metric combination. All models include PSPS event exposure, lag₀₋₃ day wildfire PM_{2.5} exposure, an interaction term between PSPS event and wildfire PM_{2.5} exposure, and a spline on mean daily temperature. The absolute metric reflects the number of individuals exposed to a PSPS event, while the relative metric reflects the severity of the event. COPD, chronic obstructive pulmonary disease. **Note: The estimate for the interaction effect represents the additional multiplicative effect of joint exposure to wildfire PM_{2.5} and PSPS event on the outcome of interest. It should not be interpreted as an odds ratio in isolation, but is rather a ratio of odds ratios. PSPS, public safety power shutoff; COPD, chronic obstructive pulmonary disease*

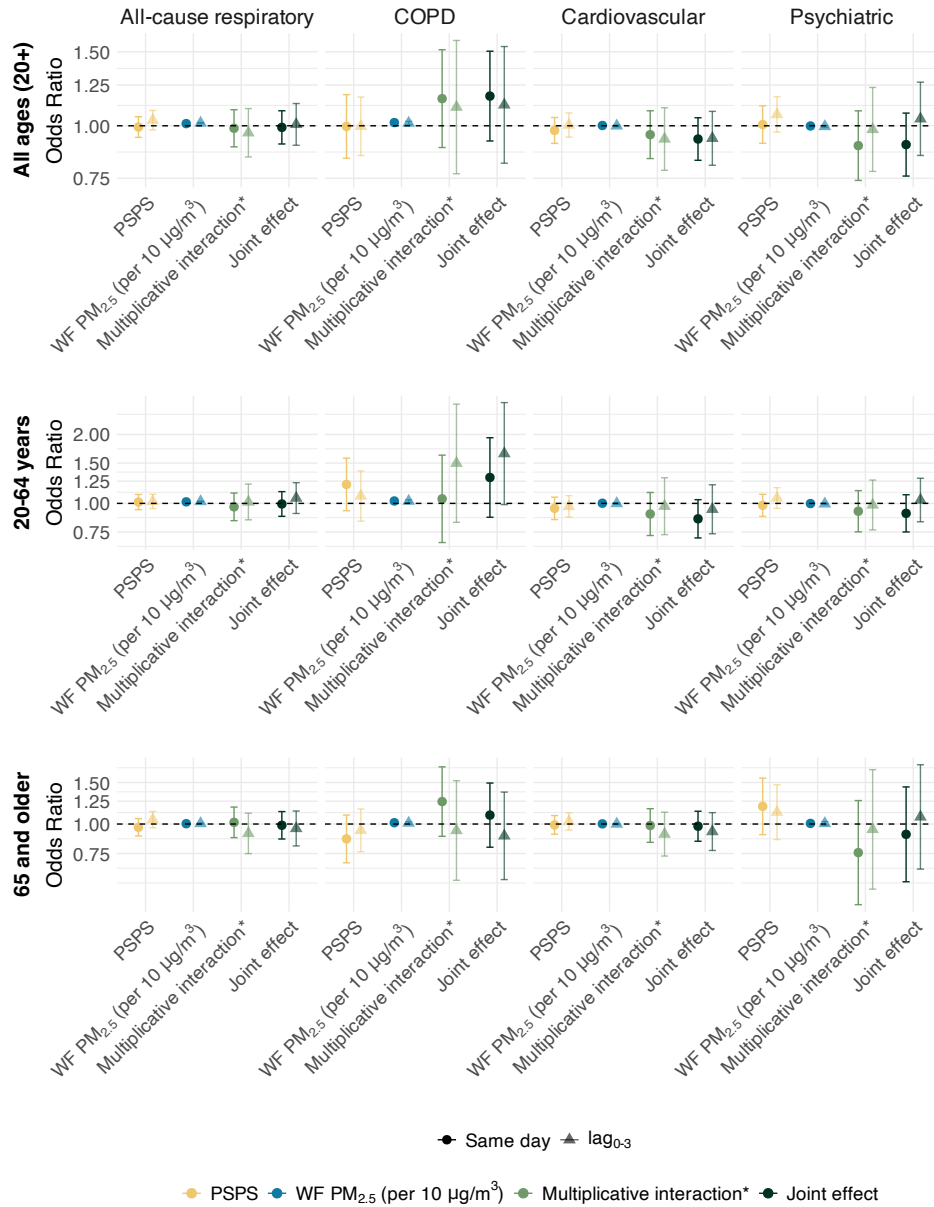


Figure 2.8: Effect estimates for moderate PSPS exposure (absolute), wildfire PM_{2.5} exposure, and cause-specific healthcare encounters, by age. Odds ratios and 95% confidence intervals for the association between zip code-level moderate PSPS events (absolute metric) and all-cause respiratory-, COPD-, cardiovascular-, and psychiatric-related emergency department visits and hospital admissions in California from 2013–2019 by age group. Estimates are from eight separate conditional logistic regression models, including one for each health endpoint – exposure metric combination. All models include PSPS event exposure, lag₀₋₃ day wildfire PM_{2.5} exposure, an interaction term between PSPS event and wildfire PM_{2.5} exposure, and a spline on mean daily temperature. The absolute metric reflects the number of individuals exposed to a PSPS event, while the relative metric reflects the severity of the event. COPD, chronic obstructive pulmonary disease. **Note: The estimate for the interaction effect represents the additional multiplicative effect of joint exposure to wildfire PM_{2.5} and PSPS event on the outcome of interest. It should not be interpreted as an odds ratio in isolation, but is rather a ratio of odds ratios. PSPS, public safety power shutoff; COPD, chronic obstructive pulmonary disease*

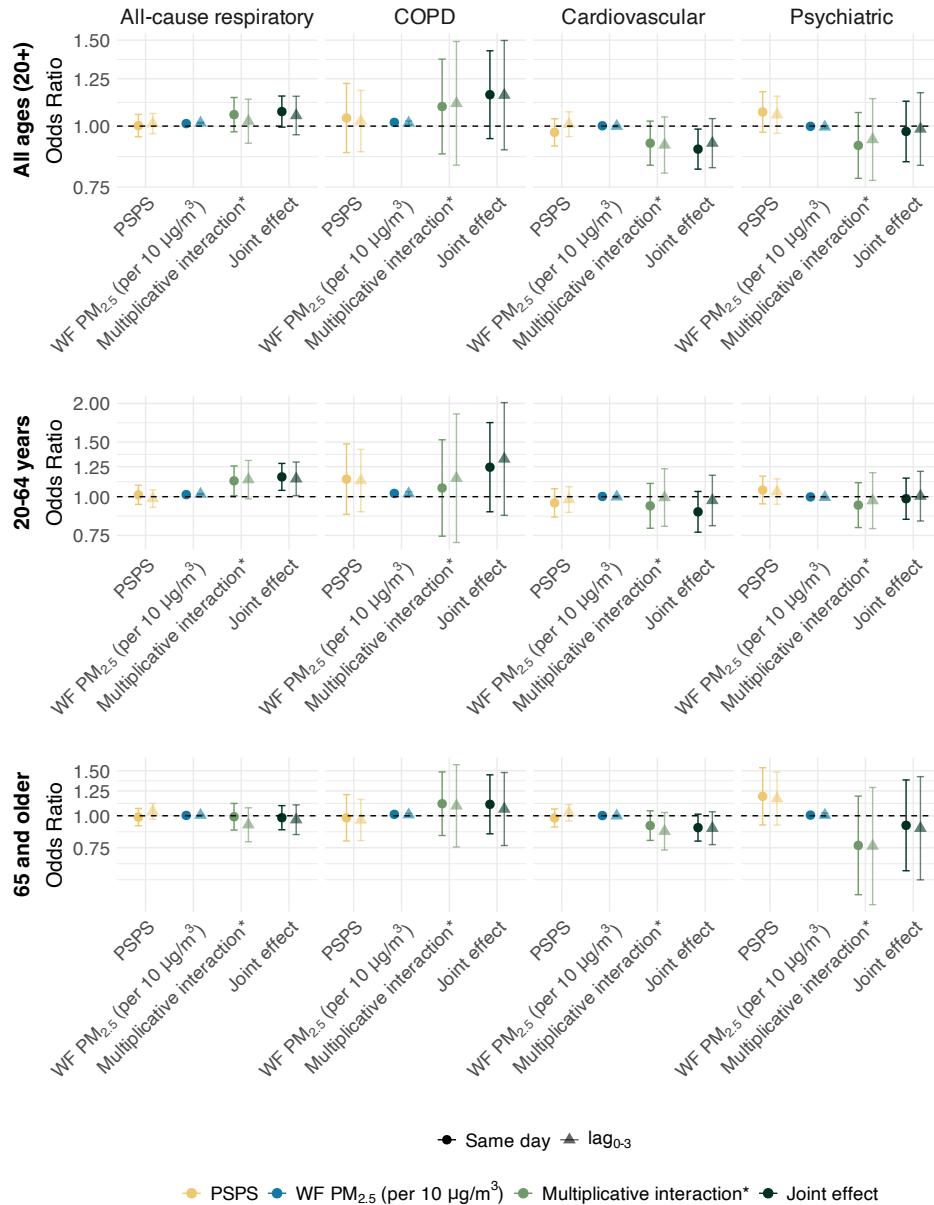


Figure 2.9: Effect estimates for moderate PSPS exposure (relative), wildfire PM_{2.5} exposure, and cause-specific healthcare encounters, by age. Odds ratios and 95% confidence intervals for the association between zip code-level moderate PSPS events (relative metric) and all-cause respiratory-, COPD-, cardiovascular-, and psychiatric-related emergency department visits and hospital admissions in California from 2013–2019 by age group. Estimates are from eight separate conditional logistic regression models, including one for each health endpoint – exposure metric combination. All models include PSPS event exposure, lag₀₋₃ day wildfire PM_{2.5} exposure, an interaction term between PSPS event and wildfire PM_{2.5} exposure, and a spline on mean daily temperature. The absolute metric reflects the number of individuals exposed to a PSPS event, while the relative metric reflects the severity of the event. COPD, chronic obstructive pulmonary disease. **Note: The estimate for the interaction effect represents the additional multiplicative effect of joint exposure to wildfire PM_{2.5} and PSPS event on the outcome of interest. It should not be interpreted as an odds ratio in isolation, but is rather a ratio of odds ratios. PSPS, public safety power shutoff; COPD, chronic obstructive pulmonary disease*

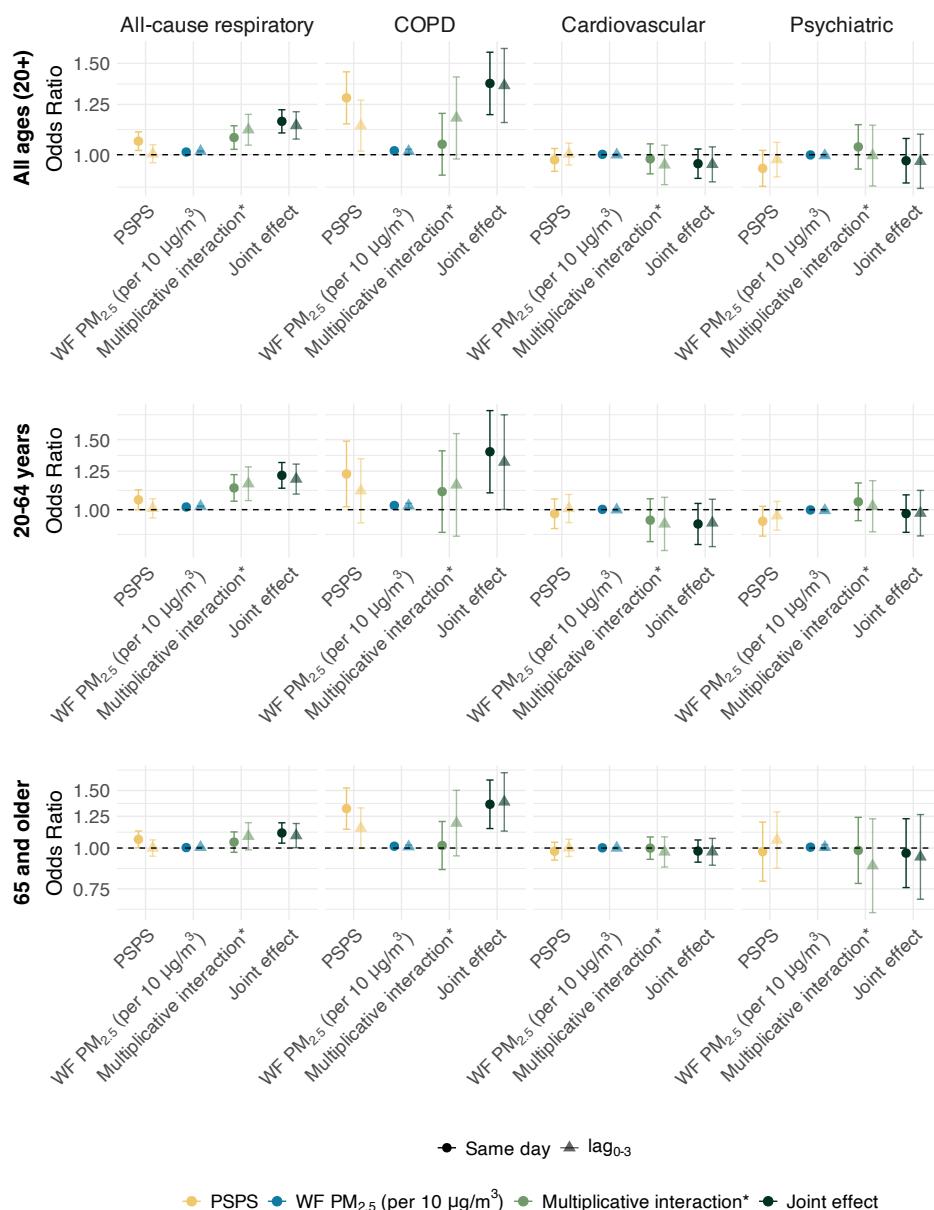


Figure 2.10: Effect estimates for severe PSPS exposure (absolute), wildfire PM_{2.5} exposure, and cause-specific healthcare encounters, by age. Odds ratios and 95% confidence intervals for the association between zip code-level severe PSPS events (absolute metric) and all-cause respiratory-, COPD-, cardiovascular-, and psychiatric-related emergency department visits and hospital admissions in California from 2013–2019 by age group. Estimates are from eight separate conditional logistic regression models, including one for each health endpoint – exposure metric combination. All models include PSPS event exposure, lag₀₋₃ day wildfire PM_{2.5} exposure, an interaction term between PSPS event and wildfire PM_{2.5} exposure, and a spline on mean daily temperature. The absolute metric reflects the number of individuals exposed to a PSPS event, while the relative metric reflects the severity of the event. COPD, chronic obstructive pulmonary disease. **Note: The estimate for the interaction effect represents the additional multiplicative effect of joint exposure to wildfire PM_{2.5} and PSPS event on the outcome of interest. It should not be interpreted as an odds ratio in isolation, but is rather a ratio of odds ratios. PSPS, public safety power shutoff; COPD, chronic obstructive pulmonary disease*

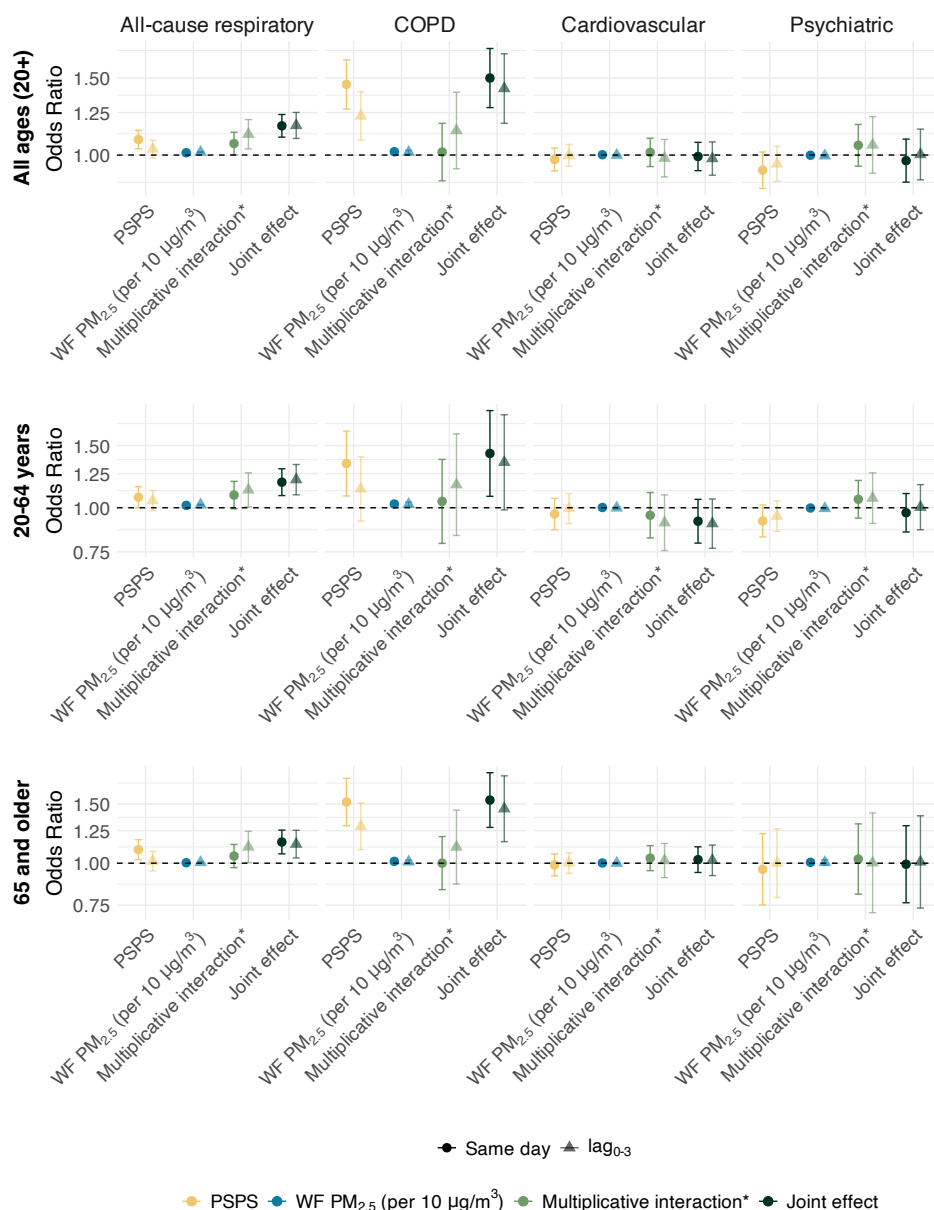


Figure 2.11: Effect estimates for severe PSPS exposure (relative), wildfire PM_{2.5} exposure, and cause-specific healthcare encounters, by age. Odds ratios and 95% confidence intervals for the association between zip code-level severe PSPS events (relative metric) and all-cause respiratory-, COPD-, cardiovascular-, and psychiatric-related emergency department visits and hospital admissions in California from 2013–2019 by age group. Estimates are from eight separate conditional logistic regression models, including one for each health endpoint – exposure metric combination. All models include PSPS event exposure, lag₀₋₃ day wildfire PM_{2.5} exposure, an interaction term between PSPS event and wildfire PM_{2.5} exposure, and a spline on mean daily temperature. The absolute metric reflects the number of individuals exposed to a PSPS event, while the relative metric reflects the severity of the event. COPD, chronic obstructive pulmonary disease. **Note: The estimate for the interaction effect represents the additional multiplicative effect of joint exposure to wildfire PM_{2.5} and PSPS event on the outcome of interest. It should not be interpreted as an odds ratio in isolation, but is rather a ratio of odds ratios. PSPS, public safety power shutoff; COPD, chronic obstructive pulmonary disease*

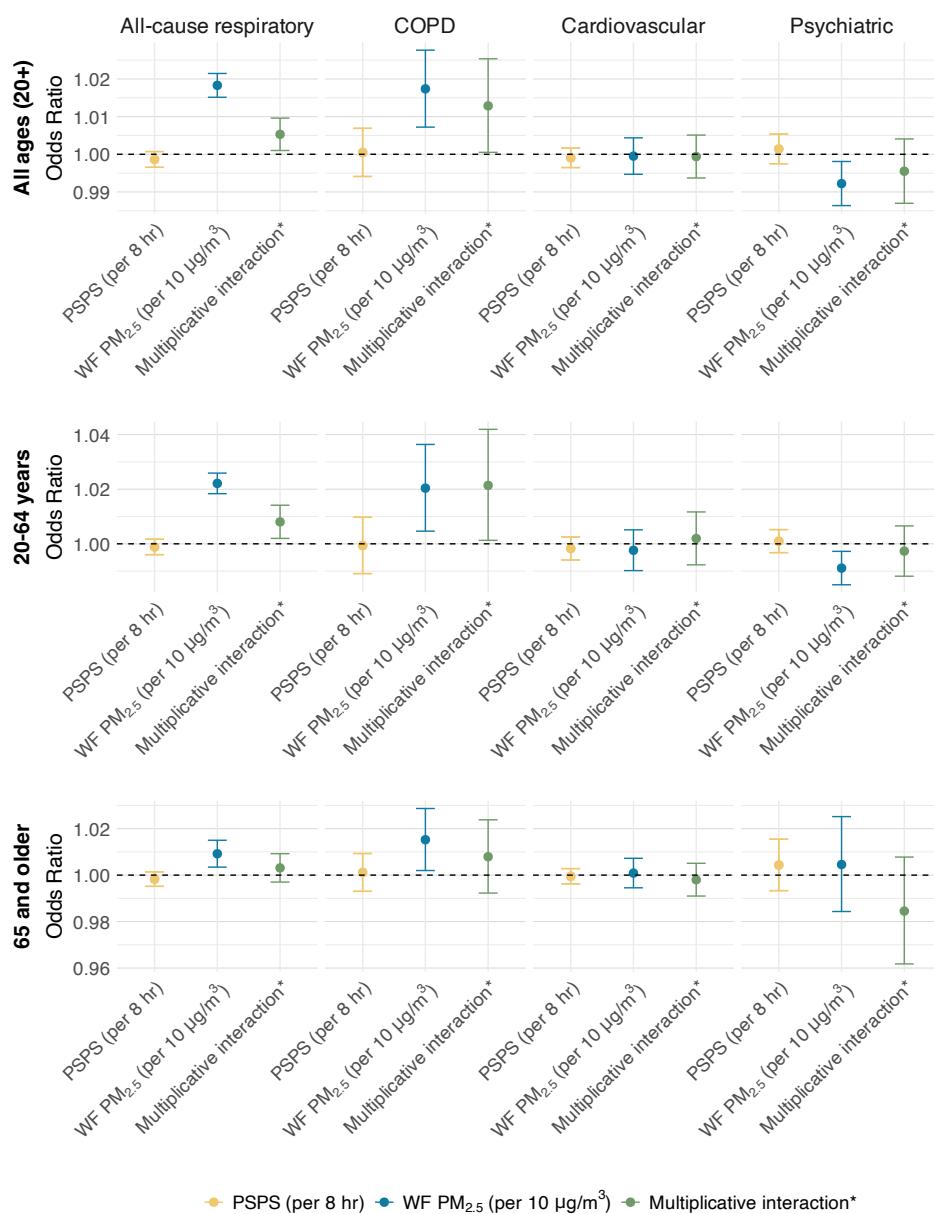


Figure 2.12: Secondary analysis: effect estimates for PSPS exposure (1 week duration), wildfire PM_{2.5} exposure, and cause-specific healthcare encounters, by age. Odds ratios and 95% confidence intervals for the association between zip code-level PSPS event duration and all-cause respiratory-, COPD-, cardiovascular-, and psychiatric-related emergency department visits and hospital admissions in California from 2013–2019 by age group. Estimates are from four separate conditional logistic regression models – one for each health endpoint. All models include PSPS duration, lag 0-6 day wildfire PM_{2.5} exposure, an interaction term between PSPS duration and wildfire PM_{2.5} exposure, and a spline on mean daily temperature. **Note: The estimate for the interaction effect represents the additional multiplicative effect of joint exposure to wildfire PM_{2.5} and PSPS event on the outcome of interest. It should not be interpreted as an odds ratio in isolation, but is rather a ratio of odds ratios. PSPS, public safety power shutoff; COPD, chronic obstructive pulmonary disease*

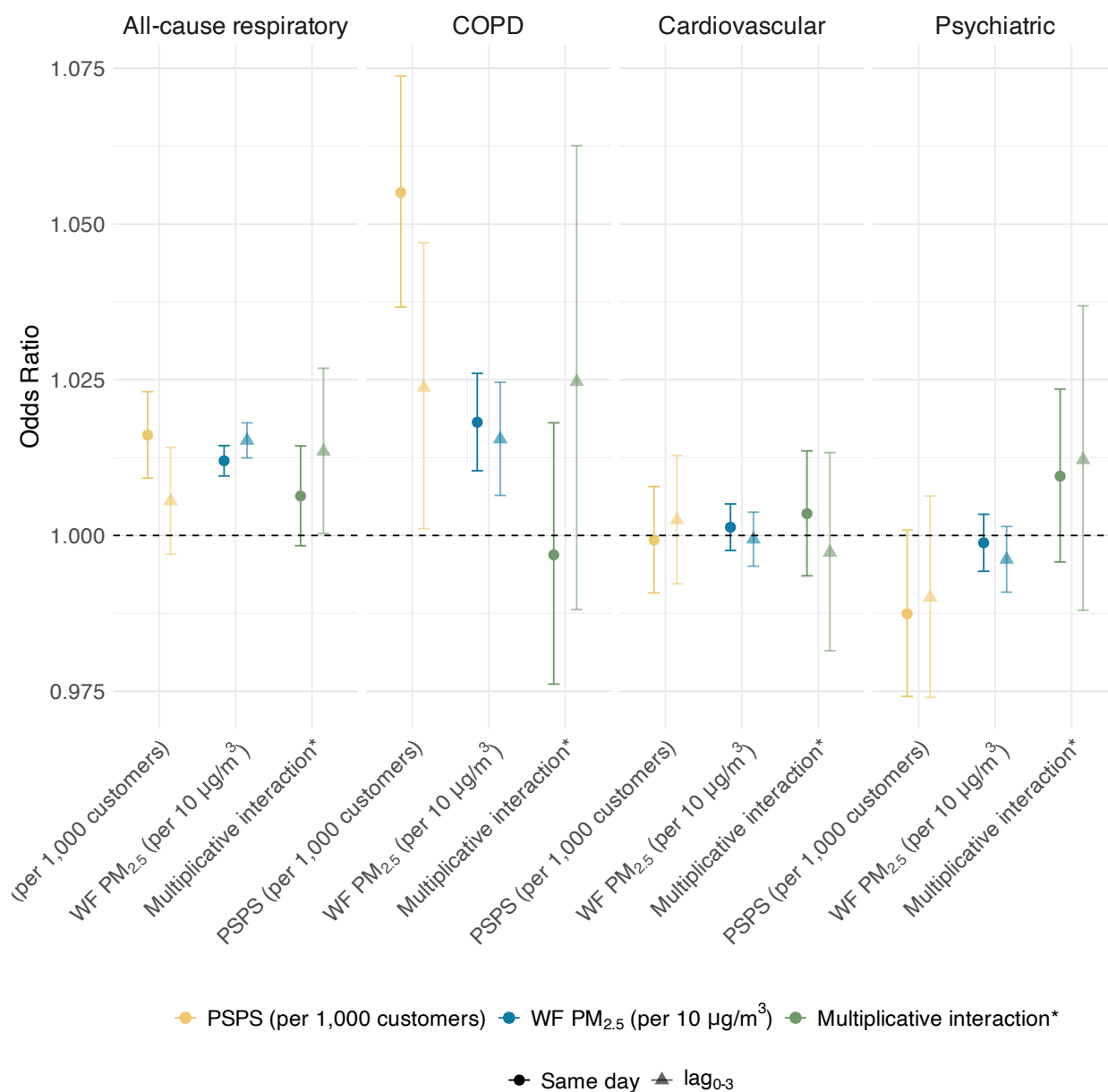


Figure 2.13: Sensitivity analysis: effect estimates for PSPS exposure (continuous, parameterized as duration of exposure in hours), wildfire PM_{2.5} exposure, and cause-specific healthcare encounters, by age. Odds ratios and 95% confidence intervals for the association between zip code-level PSPS customers impacted (continuous) and all-cause respiratory-, COPD-, cardiovascular-, and psychiatric-related emergency department visits and hospital admissions in California from 2013–2019 by age group. Estimates are from four separate conditional logistic regression models – one for each health endpoint. All models include PSPS customers impacted, lag 0-6 day wildfire PM_{2.5} exposure, an interaction term between PSPS duration and wildfire PM_{2.5} exposure, and a spline on mean daily temperature. **Note: The estimate for the interaction effect represents the additional multiplicative effect of joint exposure to wildfire PM_{2.5} and PSPS event on the outcome of interest. It should not be interpreted as an odds ratio in isolation, but is rather a ratio of odds ratios. PSPS, public safety power shutoff; COPD, chronic obstructive pulmonary disease*

CHAPTER 3

AIM 2. HEALTHCARE UTILIZATION FOLLOWING THE 2025 LA FIRES: WILDFIRE SMOKE EXPOSURE AND EVACUATION IMPACTS

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3.1 Abstract.

Background. The January 2025 Los Angeles (LA) fires forced evacuations and degraded air quality, with potential impacts on acute healthcare utilization. We aimed to determine whether wildfire smoke exposure or evacuation changed rates of acute emergency department (ED) or inpatient healthcare utilization for multiple health endpoints following the LA fires.

Methods. This cohort study used electronic health care data from Kaiser Permanente Southern California (KPSC) ED and inpatient settings from November-January 2022–2025. We assigned exposure to residential census tracts from January 7-13, 2025: (1) minimal; (2) moderate wildfire fine particulate matter (PM_{2.5}) and (3) high wildfire PM_{2.5}, based on estimates derived from National Oceanic and Atmospheric Administration HYSPLIT trajectories and air pollution monitors; and (4) evacuated, based on evacuation zones. Daily ED and inpatient visit rates across 5 categories: all-cause, cardiovascular, injury, neuropsychiatric, and respiratory. We employed a 2-stage interrupted time-series model to estimate changes in healthcare utilization rates after the fires.

Results. This study included 3.7 million KPSC members (median age of 42years) meeting enrollment criteria. Healthcare utilization among KPSC members changed during the week following the LA fires' ignition. In high smoke-exposed tracts, cardiovascular and neuropsychiatric ED rates increased (cardiovascular: 4.3% [0.6%, 18.6%]; neuropsychiatric: 7.7% [-1.8%, 19.0%]), as did cardiovascular inpatient visit rates (5.3% [-1.2%, 17.2%]). Respiratory-related hospital visits declined in most areas. However, in tracts with heavy smoke exposure, the pattern was different: ED visit rates did not increase, but inpatient visits did on the first day post-ignition and stayed elevated for the following week. Among evacuated tracts, overall care-seeking declined. Comparing healthcare utilization across evacuated tracts from the similarly-sized Eaton and Palisades fires, we found reduced all-cause care-seeking in the Eaton evacuation zone but elevated care-seeking in the Palisades evacuation zone.

Discussion. The 2025 LA fires were an unprecedented disaster that impacted healthcare-seeking

behaviors. Areas with high smoke exposure, that were not evacuated, saw increased cardiovascular and neuropsychiatric care, while care was reduced in evacuated tracts—likely reflecting disrupted care and unmet need. These heterogeneous impacts of the LA fires demonstrate the need for targeted healthcare planning based on community-specific wildfire effects.

3.2 Introduction.

January 7, 2025 marked the ignition of the Eaton and Palisades fires, closely followed by several other large fires, in Los Angeles (LA) County, California.^{12,114,115} Strong Santa Ana winds fueled the fires, blowing smoke across the region and causing fine particulate matter (PM_{2.5}) concentrations to soar as high as 400 µg/m³ during the days following ignition.¹¹⁶ Researchers estimate that the fires burned > 38,000 acres, destroyed > 16,000 structures, led to the evacuation of > 180,000 people, and directly killed at least 29 people.^{19,114} However, the full health burden likely extends beyond these immediate, direct fatalities. For example, one study estimated > 440 excess deaths in LA County following fire ignition.¹¹⁷

Though much remains unknown about the underlying mechanisms by which wildfires affect health, the current literature points to multiple pathways - including smoke inhalation, stress, destruction of property and communities, and displacement.¹² Two major components of wildfire disasters that drive these pathways are elevated PM_{2.5} concentrations and evacuation. Wildfire PM_{2.5} triggers systemic inflammation and oxidative stress associated with adverse health, including increased respiratory and cardiovascular morbidity, neuropsychiatric outcomes, and all-cause mortality.^{16,22,29}, as well as stress and behavior change,^{16,23}. Evacuation also causes stress, poses physical hazards, and disrupts healthcare access^{12,22} and, as such, may contribute to adverse neuropsychiatric outcomes, injuries, and exacerbate chronic conditions.^{12,33,35,36}

During the 2025 LA fires, elevated PM_{2.5} spread across much of LA County and > 180,000 people were under evacuation orders.^{12,19,114,116} In addition to causing elevated excess mortality,¹¹⁷ a recent study reported surging cardiorespiratory emergency encounters (24-46% increases) in the 90 days following ignition at Cedars-Sinai (the largest adult medical center in LA County).¹¹⁸ Across Kaiser Permanente Southern California (KPSC), outpatient and virtual visits for cardiorespiratory conditions increased 27-42% during the week post-fire ignition, with ignition-day increases in neuropsychiatric (28-31%) and injury (18-26%) encounters.¹⁹ Notably, syndromic surveillance data showed some evidence of decreased overall emergency department (ED) encounters during the first six days post-ignition.¹¹⁹ None of these studies evaluated healthcare utilization in relation

to major health-harmful mechanisms, smoke exposure and evacuation, which may help to reconcile the different impacts observed and are essential to understand in appropriately allocating resources for healthcare planning, adaptation, and response.

Here, we examined changes in acute healthcare utilization among KPSC members during the week following the January 2025 LA fires' ignition. We estimated associations between exposure and healthcare utilization following the LA fires, distinguishing between wildfire PM_{2.5} and evacuation zone exposure to better understand the underlying mechanisms.

3.3 Methods.

3.3.1 Study Design and Population.

KPSC serves more than 4.7 million patients across 10 counties in Southern California, and this study included patients with continuous enrollment from November 1, 2022 to January 13, 2025 who met other inclusion criteria (Figure 3.1). Since KPSC is an integrated healthcare system, its electronic health record (EHR) database contains complete longitudinal information on patient addresses and diagnoses - allowing us to construct a cohort of KPSC members to follow for the duration of the study period. Using a quasi-experimental study design, we leveraged the timing of the LA Fires to study attributable changes in healthcare utilization in a two-stage interrupted time series (ITS) analysis. This study followed the Strengthening the Reporting of Observational

Studies in Epidemiology (STROBE) guidelines. The protocol was approved by the KPSC and WIRB–Copernicus Group institutional review boards, which waived the informed consent requirement.

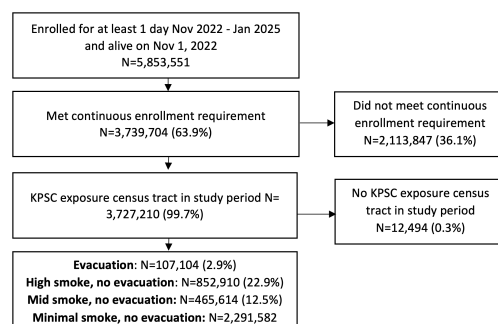


Figure 3.1: Kaiser Permanente Southern California cohort inclusion/exclusion. Flowchart depicting inclusion into the cohort of Kaiser Permanente Southern California members included in this study. For each year, patients were required to have coverage November through January (of the next year) – allowing for up to 30 days gap. Patients were also required to be enrolled for all three years: November 2022 - January 2025 – unless someone ended their enrollment due to death prior to 2025.

3.3.2 Exposure and covariates.

Wildfire PM_{2.5}.

During the January 2025 LA fires, strong Santa Ana winds dispersed smoke unevenly across the region, meaning that models extrapolating PM_{2.5} concentrations from sparse US EPA ground-monitoring stations did not accurately represent population-level exposure to wildfire PM_{2.5}. In order to integrate known meteorological drivers of smoke dispersion, we leveraged National Oceanic and Atmospheric Administration's (NOAA) Air Resources Laboratory (ARL) Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model via Real-time Environmental Applications and Display sYstem (READY) platform.^{120,121} Because only smoke from the Eaton fire affected the KPSC catchment, we estimated census tract-level exposure to wildfire PM_{2.5} using HYSPLIT trajectories from the Eaton fire centroid (Supplemental methods). We validated exposure categories using observed PM_{2.5} at ground monitors in LA County.

We categorized census tracts into three levels of wildfire PM_{2.5} exposure based on the number of HYSPLIT trajectories they intersected. Categories included: (1) minimal, (2) moderate, or (3) high levels of wildfire PM_{2.5} exposure during the week following January 7 (Figure 3.2, Supplemental methods).

Evacuation.

We combined data from LA County's Integrated Public Alert and Warning System (IPAWS) and Ventura County Department of Emergency Services to identify census tracts that intersected with evacuation order or warning zones between January 7 and 10, 2025.

Overall exposure assessment.

Based on our wildfire PM_{2.5} and evacuation categories, we constructed a census tract-level exposure dataset with four exposure categories: (1) minimal wildfire PM_{2.5} with no evacuation, (2)

moderate wildfire PM_{2.5} with no evacuation, (3) high wildfire PM_{2.5} with no evacuation, and (4) evacuation regardless of smoke exposure (Supplemental methods).

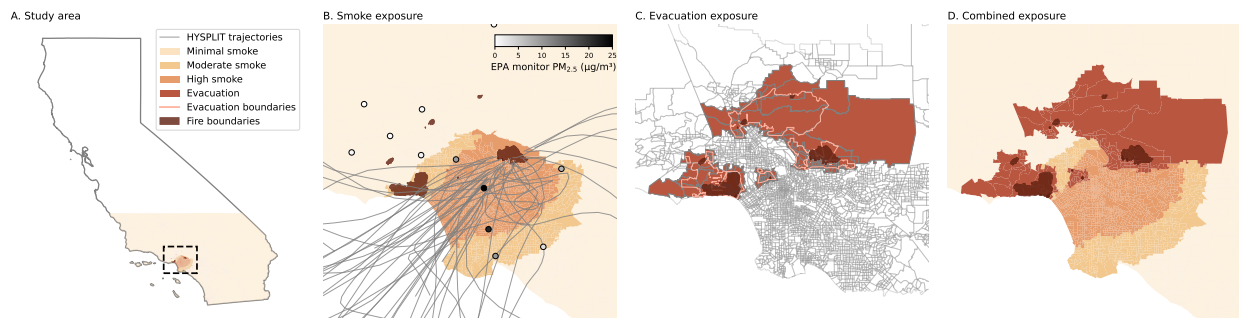


Figure 3.2: Exposure assessment for wildfire PM_{2.5} and evacuation following the 2025 Los Angeles Fires. Panel A: KPSC’s catchment area, with a dashed black box showing the subset of the KPSC catchment depicted in panels B-D. Panel B: Wildfire PM_{2.5} exposure estimated using National Oceanic and Atmospheric Administration’s (NOAA) Air Resources Laboratory (ARL) Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model trajectories. Exposure was determined based on the number of trajectories intersecting a census tract. We categorized wildfire PM_{2.5} exposure as (1) minimal, (2) moderate, and (3) high. EPA monitoring station PM_{2.5} is shown for reference, but was not used for exposure assessment. Panel C: Evacuation zone perimeters in pink are shown on top of the evacuation-exposed census tracts in orange. A census tract was considered evacuated if any part of it intersected an evacuation zone. Wildfire burn zones (red) are included for reference. Panel D: Overall exposure categories: (1) minimal smoke, (2) moderate smoke, (3) high smoke, and (4) evacuation (regardless of smoke exposure).

Covariates.

We included time-varying covariates in all models: county-level weekly influenza, respiratory syncytial virus (RSV), and SARS-CoV-2 from wastewater data collected by the LA County Department of Public Health. Additionally, we used 4km² resolution gridMET (Gridded Surface Meteorological) data, aggregated to the census tract level, to adjust for daily temperature (minimum and maximum), humidity, wind velocity, and surface downward shortwave radiation.

3.3.3 Outcomes.

Outcomes included daily rates of ED visits (without admission) and hospital admissions by KPSC members. Using *International Classification of Diseases*, Tenth Revision codes, we included visits

for all-cause, cardiovascular [I00-I99], injury [S00-T88], neuropsychiatric [F01-F99], and respiratory [J00-J99] conditions.¹⁹ We aggregated visits by type, cause, day, and wildfire exposure category.

3.3.4 Statistical Analysis.

We modeled healthcare utilization using data from three consecutive November - January periods (2022 - 2025) and predicted health outcomes over a 7-day period following fire ignition (January 7 - January 13, 2025). We used a two-stage interrupted time-series design that leveraged machine-learning methods to estimate the wildfire-attributable change in visit rates following the LA fires.^{19,61}

Parameterization of models for this analysis.

We separately modeled combinations of exposure category (minimal smoke, moderate smoke, high smoke, evacuation), encounter type (ED, inpatient), and outcome (all-cause, cardiovascular, injury, neuropsychiatric, and respiratory).

Because the ITS design capitalizes on random timing of an event (in this case, the LA Fires), time-invariant covariates are inherently controlled. However, we controlled for time-varying covariates, as they can affect healthcare utilization rates concurrently with the event. Specifically, we included covariates for federal holidays, time period, day of week, and month, as well as previously-described daily meteorological variables from gridMET⁹³ and weekly wastewater surveillance data on influenza, RSV, and SARS-CoV-2 levels.¹²²

Using a time-series split approach, we split the data into training and testing sets. The purpose of this splitting is to assess out-of-sample predictive performance and ensure the model generalizes beyond the data used for training. This approach allows us to use our model to generate a reliable counterfactual (expected) time series to compare to the observed time series (Figure 3.7). To balance generalizability with model specificity, we initially used the same hyperparameter ranges for all models, then tailored ranges for specific models. We selected the optimal hyperparameter set for each model by minimizing RMSE across folds, and evaluated performance using mean absolute

percentage error, mean absolute scaled error, and R^2 (more details in Supplemental methods).

For these optimized models, we estimated 95% empirical confidence intervals using Monte Carlo simulation with 1,000 iterations, using the 2.5th and 97.5th percentiles as the lower and upper bounds. Excess visit rates (per 100,000 enrollees per day) were calculated as the daily difference between observed and predicted rates. Results are presented as the percent excess rate alongside the mean excess rate over the study period.

To examine fire-specific effects, we conducted a secondary analysis restricting the evacuation exposure to census tracts affected by the Eaton or Palisades fires separately.

Analyses were conducted using R Statistical Software version 4.4.1 and Python version 3.12.2, and all code is available on GitHub.

3.4 Results.

We identified 3,717,210 KPSC members with median age 42 years residing in 4,876 census tracts across the 10 counties of Southern California (Figure 3.2 panel A and Table 3.1). Members were 52.2% female, and 29.0% identified as non-Hispanic white, 7.8% as non-Hispanic Black, 11.5% as non-Hispanic Asian, and 43.8% as Hispanic. 852,910 resided in high-smoke census tracts (maximum daily average Environmental Protection Agency [EPA]-reported $PM_{2.5} = 28.57 \mu g/m^3$), 465,614 in moderate-smoke census tracts (maximum EPA-reported $PM_{2.5} = 7.69 \mu g/m^3$), 107,104 in evacuated census tracts (Figure 3.2, panels B-D; Table 3.1 and Table 3.2).

3.4.1 Emergency department encounters.

No KPSC EDs were located in tracts considered evacuated in the present analysis (Figures 3.5 and 3.6), but the rate of all-cause ED visits among evacuated members decreased over the week-long period following fire onset (Figure 3.3 and Figure 3.9; Tables 3.3 and 3.4). Further, despite no change averaged across the week, neuropsychiatric visit rates among members in evacuated

tracts were elevated on several days, with mid-week excess visit rates on par with or exceeding that of high-smoke tracts (Figures 3.8 and 3.9; Tables 3.3, 3.4, 3.9, and 3.10).

Among those living in high-smoke tracts, cardiovascular and neuropsychiatric ED visit rates were elevated during the first week following fire onset, with 4.3% [0.6%, 18.6%] and 7.7% [-1.8%, 19.0%] excess cardiovascular and neuropsychiatric visit rates, respectively (Figures 3.8 and 3.9; Tables 3.9 and 3.10).

	Total (N=3,717,210)	Minimal smoke (N=2,291,582)	Moderate smoke (N=465,614)	High smoke (N=852,910)	Evacuation (N=107,104)
Age in years, median (IQR)	42 (21, 62)	42 (21, 61)	44 (22, 62)	42 (23, 61)	48 (25, 66)
Sex, n (%)					
Female	1,941,970 (52.2%)	1,192,928 (52.1%)	243,598 (52.3%)	449,982 (52.8%)	55,462 (51.8%)
Male	1,774,871 (47.7%)	1,098,432 (47.9%)	221,976 (47.7%)	402,835 (47.2%)	51,628 (48.2%)
Other	167 (<0.1%)	94 (<0.1%)	23 (<0.1%)	45 (<0.1%)	5 (<0.1%)
Unknown	202 (<0.1%)	128 (<0.1%)	17 (<0.1%)	48 (<0.1%)	9 (<0.1%)
Race and ethnicity, n (%)					
Hispanic	1,627,406 (43.8%)	934,408 (40.8%)	185,024 (39.7%)	480,048 (56.3%)	27,926 (26.1%)
Non-Hispanic Asian	426,054 (11.5%)	232,307 (10.1%)	86,636 (18.6%)	90,849 (10.7%)	16,262 (15.2%)
Non-Hispanic Black	290,701 (7.8%)	141,276 (6.2%)	36,645 (7.9%)	106,241 (12.5%)	6,539 (6.1%)
Non-Hispanic white	1,078,707 (29.0%)	802,187 (35.0%)	116,563 (25.0%)	113,361 (13.3%)	46,596 (43.5%)
Unknown	173,378 (4.7%)	108,882 (4.8%)	22,462 (4.8%)	36,503 (4.3%)	5,531 (5.2%)
Other	120,964 (3.3%)	72,522 (3.2%)	18,284 (3.9%)	25,908 (3.0%)	4,250 (4.0%)

Table 3.1: Demographic characteristics of study participants. Number of Kaiser Permanente Southern California patients included in this study by exposure category (minimal smoke, moderate smoke, high smoke, evacuation). *Note: “Other” racial and ethnic group includes people of multiple races, Native American and Alaskan Native, Pacific Islander, other, and unknown race and ethnicity.*

Injury-related ED visit rates were reduced 8-10% across all exposure groups, while respiratory ED visit rate were uniformly unchanged (Figure 3.3 and Figure 3.9; Tables 3.3, 3.4, 3.9, 3.10, 3.11, 3.12).

3.4.2 Inpatient admissions.

For all-cause admissions, effect magnitudes were small relative to ED visit rates, and most cause-specific changes were limited to the high-smoke group.

Despite no change in respiratory ED visit rates for any group, we observed a spike in respiratory inpatient admissions among those in high-smoke tracts on day 1, which remained elevated throughout the first week (11.9% [-1.3%, 25.3%]). Respiratory admissions among members in evacuated tracts decreased on day 1 and were otherwise unchanged (Figure 3.3 and Figures 3.8 and 3.9; Tables 3.19, 3.20, 3.13, 3.14).

All-cause, cardiovascular, and neuropsychiatric admission rates were modestly elevated among high-smoke tracts toward the end of the first week (5.3% [-1.2%, 17.2%]) (Tables 3.19 and 3.20). Conversely, neuropsychiatric admission rates among those in evacuated tracts and moderate-smoke tracts declined during the first two days post-ignition. Injury admission rates were largely null, with the exception of a single large increase among moderate-smoke tracts mid-week (-4.9% [-11.6%, 6.9%]) (Tables 3.19, 3.20, 3.21, 3.22, 3.13, 3.14).

3.4.3 Evacuation-stratified analysis.

When stratifying by evacuation zone, we observed differential patterns of care-seeking between Eaton and Palisades fires (Figures 3.11, and 3.10; Tables 3.5, 3.6, 3.7, 3.8, 3.15, 3.16, 3.17, 3.18). All-cause ED and inpatient visit rates were reduced among Eaton evacuation zone members (ED: -11.8% [-27.6%, -4.3%]; inpatient: -16.1% [-35.5%, 3.5%]), while Palisades members showed potentially elevated utilization across both settings (ED: 7.9% [-2.6%, 27.0%]; inpatient: 14.4% [-4.6%, 34.5%]). Cause-specific estimates were largely null across both fire areas, with the exception of reduced respiratory ED visit rates and cardiovascular inpatient admissions among Eaton members (Figures 3.11, 3.10, and 3.8).

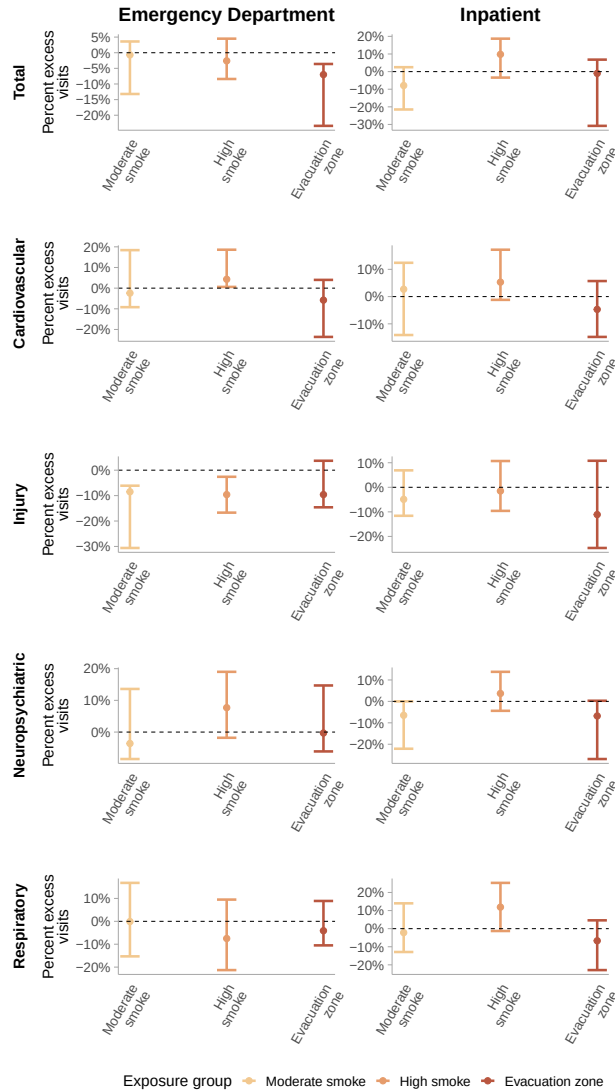


Figure 3.3: Cause-specific excess emergency department and inpatient visits due to wild-fire PM_{2.5} and evacuation. Association between census tract-level (1) moderate smoke, (2) high smoke, and (3) evacuation exposure during the 2025 LA fires and percent change in excess all-cause and cause-specific emergency department and inpatient visit rates in the Kaiser Permanente Southern California catchment area from January 7-13, 2025. Cause-specific visits included cardiovascular, injury, neuropsychiatric, and respiratory. Estimates are from an interrupted time-series design that leveraged machine learning methods to estimate the wildfire-attributable change in visit rates following the LA fires. Each encounter type/exposure category/health endpoint was modeled separately using data from November-January 2022-2025 and time-varying covariates to model pre-fire trends. These 40 separate models were then used to predict expected post-LA fire trends. By comparing the post-fire trends predicted from our models, which served as a counterfactual, to observed post-fire trends, we calculated the percent excess visit rates attributable to the fires. 95% empirical confidence intervals were computed using Monte Carlo simulation with 1,000 iterations, using the 2.5th and 97.5th percentiles as the lower and upper bounds.

3.5 Discussion.

In this interrupted time series analysis of 3,717,210 KPSC members in the week following the January 2025 LA fires' ignition, we found divergent patterns in healthcare utilization across smoke and evacuation exposure groups. In tracts exposed to high smoke, cardiovascular and neuropsychiatric ED visit and cardiovascular and respiratory admission rates were elevated. Visit rates were unchanged for those exposed to moderate smoke, as well as for respiratory ED visits across all exposure groups. We observed reduced rates of ED utilization in evacuated tracts and of injury-specific ED visits across all tracts.

We interpret these findings in the context of healthcare seeking across all care settings at KPSC following the fires. In previous work, we estimated a 36-45% increase in respiratory- and cardiovascular-related virtual care visits, in addition to elevations in outpatient visits ranging from 18-31% for cardiovascular, injury, neuropsychiatric, and respiratory endpoints among KPSC members living within 20km of a burn zone or within LA county.¹⁹ Conversely, in this study, we observed more heterogeneous care-seeking, including reductions in ED and inpatient settings for some groups.

Furthermore, an interrupted time series analysis of LA County mortality estimated 440 excess deaths attributable to the fires, representing nearly 7% excess mortality over a 4-week period.¹¹⁷ Taken together with the increases in KPSC virtual and outpatient care utilization,¹⁹ our findings suggest that among high smoke-exposed members, some care may have been diverted from the ED to lower acuity virtual or outpatient care settings, with some care never taking place due to out-of-hospital patient mortality.

Our findings of elevated care-seeking among high-smoke-exposed, but not moderate-smoke-exposed, individuals are consistent with mixed prior literature on wildfire PM_{2.5} and cardiovascular diseases.^{16,22,34} Importantly, one single-site study following the LA fires found a 46% increase in myocardial infarction ED encounters within 90 days post-ignition.¹¹⁸ For neuropsychiatric outcomes, several^{26,27,123}, but not all,¹²⁴ studies indicate elevated acute care-seeking following wildfire PM_{2.5} exposure. Further, substantial evidence links wildfire disaster exposure to elevated rates of PTSD, depression,

and anxiety.^{29,125,126} Combined with our prior study,¹⁹ we have identified universally elevated care-seeking – across virtual, outpatient, ED, and inpatient care settings – for cardiovascular and neuropsychiatric endpoints at KPSC following the LA fires.

Despite elevated injury-related virtual care utilization among KPSC members living in close ($< 10km$) proximity to burn zones,¹⁹ we did not observe elevated injury visit rates in the ED nor inpatient setting. In fact, we found reduced rates of injury-related ED visits among all smoke- or evacuation-exposed tracts. These reduced rates may be attributable to households sheltering in place^{23,127} or effective evacuation procedures – reducing motor vehicle crashes and other acute injuries expected to present to the ED.

Our findings of increased inpatient respiratory admission rates among high smoke-exposed tracts are broadly consistent with prior literature linking wildfire $PM_{2.5}$ exposure to respiratory morbidity and mortality,¹⁶ however, this signal was notably absent in our ED results. The lack of change in respiratory ED visit rates may reflect displacement of healthcare utilization to other settings, such as virtual and outpatient care, where we previously identified substantial increases at KPSC following the fires.¹⁹ Further, we saw no change ED or inpatient respiratory care among moderate smoke-exposed tracts. As the acuity of respiratory health exacerbation varies from mild wheezing in asthmatics to severe respiratory distress in those with chronic obstructive pulmonary disease (COPD), some individuals may have been able to manage their care in outpatient and virtual settings, avoiding emergency care. Our results suggest that only those with the most severe conditions, more likely to require inpatient admission, sought in-person care. Further, wildfire events have increased, and improved public health messaging may have empowered vulnerable patients – such as those living with asthma or COPD – to shelter in place, wear masks, and run air filtration systems.¹²⁸ This may have enabled many of these patients to stay home rather than go out in the smoke to seek care.

With the exception of spikes in neuropsychiatric ED visit rates – a pattern well-documented following disasters^{129–131} – evacuated KPSC tracts generally saw reductions in ED utilization, mirroring previously reported decreases in all-cause ED encounters across LA County 6 days following the 2025 LA fires' ignition.¹¹⁹ Limited research has focused on wildfire-evacuated populations, but two

small studies (< 1000 people)^{35,132} reported unmet healthcare needs and disrupted care-seeking, findings corroborated by the disaster literature.^{130,133,134} Though our study benefited from a large sample size, we could not track which patients left the area entirely and thus avoided smoke exposure, or, conversely, experienced serious impacts such as property destruction or burns that may have prevented them from seeking care. As such, the reduction in all-cause ED visits observed could be due to disrupted daily life or displacement of care from the emergency to virtual setting.^{12,114,135–137}

Despite the Eaton and Palisades fires being similarly destructive, all-cause ED and inpatient visit rates were reduced in Eaton-evacuated tracts and increased in Palisades-evacuated tracts. Further, we observed reduced respiratory ED visits and cardiovascular inpatient admissions among Eaton-evacuated members – suggesting that the null results for these endpoints in the pooled evacuation analysis may have masked meaningful reductions in the Eaton zone. Together, these patterns may reflect underlying sociodemographic differences between the areas. The median household income is higher in the Palisades compared to the Eaton evacuation zones (Palisades: \$158,140; Eaton: \$94,196),¹³⁸ which could mean that KPSC members near the Eaton fire faced greater barriers to seeking medical attention after evacuation, or a greater shift toward virtual care.

This study has several limitations. First, KPSC is an integrated healthcare system in which members rarely seek external care, which improved our ability to detect changes in healthcare utilization but might make KPSC members' care-seeking practices unrepresentative of the general population. Second, there was some exposure misclassification. We assigned exposure based on ambient conditions in residential census tracts and lacked information on whether individuals were at home or used air filtration devices during the fires. Third, we did not differentiate mandatory and voluntary evacuation orders, which may have different effects. Further, a census tract was considered evacuated regardless of smoke exposure. Future studies could consider the smoke exposure within evacuated areas as predictors of healthcare utilization. Fourth, we studied healthcare utilization, which requires an individual to seek care and access a provider, thus, we likely underestimated the fires' full health impact.

In conclusion, we found elevated cardiovascular and neuropsychiatric ED visit and cardiovascular

and respiratory admission rates among KPSC members exposed to high smoke following the LA fires' ignition. While evacuation was broadly associated with reduced ED utilization, the divergent findings across the Palisades and Eaton fire evacuation zones highlight that contextual factors can shape care-seeking behavior following disasters. By examining distinct exposure pathways, we illuminate ways in which stress and disruption may affect health differently from inhaling smoke - two common yet unique wildfire exposures. Interpreted alongside simultaneous increases in virtual and outpatient utilization and excess mortality,^{19,117} our findings suggest a bifurcated response where many KPSC members shifted care to lower-acuity settings, while those with the most serious needs were ultimately hospitalized or died. Healthcare systems preparing for an era of more frequent and intense wildfires should treat expanded cardiovascular and neuropsychiatric services, robust virtual care capacity, and targeted outreach to displaced populations not as contingencies, but as key components of disaster preparedness.

3.6 Supplemental methods.

3.6.1 Wildfire $PM_{2.5}$.

During the January 2025 LA fires, strong Santa Ana winds caused smoke to disperse rapidly and unevenly across the region, limiting the utility of sparse US Environmental Protection Agency ground monitoring stations for estimating population-level exposure. In order to include a more accurate representation of smoke exposure, we leveraged National Oceanic and Atmospheric Administration's (NOAA) Air Resources Laboratory (ARL) Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model via Real-time Environmental Applications and Display sYstem (READY) platform.^{120,121} HYSPLIT is a Lagrangian particle model widely used for atmospheric trajectory and dispersion calculations, simulating how air parcels move from an initial location based on meteorological conditions.¹²¹ To estimate wildfire smoke exposure at the census tract level, we estimated wildfire $PM_{2.5}$ transport during the LA fires using this model by initializing trajectories from the Eaton fire centroid and run using GDAS1 meteorology to simulate forward trajectories. We applied several restrictions to the trajectories:

1. excluded trajectory points at the initialization location to avoid artificially inflating exposure near the fire origin
2. terminated trajectories once they reached ground level (0m above ground level)
3. excluded trajectory points above 2,000m above ground level, as smoke at this altitude is unlikely to affect surface concentrations¹³⁹
4. limited trajectories to the first 24 hours after initialization, as smoke had dispersed beyond the study area after this period
5. included trajectories through January 14, 2025 (UTC)

After retrieving a set of points for each trajectory, we buffered each point by 20km and drew a line for each trajectory. We counted the number of buffered trajectory lines overlapping each census

tract's population-weighted centroid. To calculate population-weighted centroids for each census tract, we used the Global Human Settlement Layer.¹⁴⁰ We used population-weighted centroids rather than geometric centroids to better represent where people live within each census tract.

We validated our approach by comparing the number of overlapping buffered trajectories for a given census tract with the closest EPA ground monitoring station-measured average smoke $PM_{2.5}$ from January 7-13, 2025 (correlation = 0.92) (Figure 3.4). Average smoke $PM_{2.5}$ was estimated at EPA monitoring stations as positive anomalies in $PM_{2.5}$ on days when smoke plumes were overhead, as in Childs et al.¹⁴¹ Accordingly, we categorized census tracts into three wildfire $PM_{2.5}$ exposure levels:

1. minimal smoke: < 30 buffered trajectories overlapping centroid
2. moderate smoke: $30 - 74$ buffered trajectories
3. high smoke: ≥ 75 buffered trajectories

Finally, we reclassified tracts for which all neighboring tracts had a different exposure category to match the most common neighboring category. For example, if a tract was estimated to have mid-level smoke exposure but was surrounded on all sides by tracts with high smoke exposure, we reclassified it as having high smoke exposure.

3.6.2 Evacuation

We used data from LA and Ventura Counties to determine census tracts in the KPSC catchment area that were under evacuation orders or warnings during the LA fires.

Data from LA County.

We used data from LA County's Integrated Public Alert and Warning System (IPAWS) alerts for the January 2025 fires, including fire-related evacuation warnings and orders, as well as local

emergency alerts for LA County residents.¹⁴² We filtered these data to evacuation warnings or orders that were in effect between January 7 and 10, 2025. We defined *in effect* as after the *effective* time and before the *expires* time in the database. In cases where the "effective" time was not specified, it was assumed to be the time that the order was sent. We also focused on evacuation-related alerts and thus excluded alerts specifying that a curfew is in effect or that air quality is poor. We determined whether an alert was an evacuation order or an evacuation warning based on the "event" type specified in the dataset. However, two alerts were not categorized as "Evacuation Immediate" events but still explicitly instructed residents to "LEAVE NOW" in the message body, so we included those entries as evacuation orders.

Data from Ventura County.

Though the January 2025 fires predominantly affected LA County, the response to the Kenneth Fire, which occurred near the border of LA and Ventura Counties, was shared by both counties. The Kenneth Fire was not included in the LA County database, and we could not access spatial information on evacuation associated with it from Ventura County. As such, to ensure we had all relevant evacuation information for census tracts affected by the Kenneth Fire, we contacted the Ventura County Department of Emergency Services directly and received a shapefile and details on the sole evacuation alert issued during the study period. This single evacuation alert associated with the Kenneth Fire was a warning that was in effect January 9, 2025 from 3:48PM - 7:04PM. The Kenneth Fire evacuation area overlapped with census tracts in LA County, so we included this alert to ensure complete evacuation exposure classification for all KPSC members in the study area.

Full evacuation exposure.

We combined data from LA County and Ventura County and unioned all geographic areas that were issued an evacuation order or warning over the study period. We did not differentiate between evacuation orders and warnings due to limited sample sizes within order- and warning-specific areas. A census tract was considered evacuated if it overlapped (fully or partially) with an evacuation warning/order polygon (Figure 3.2). Evacuated census tracts were considered evacuated regardless of

smoke exposure because (1) areas that are evacuated are highly exposed to the wildfire regardless of PM_{2.5} exposure, (2) areas under evacuation orders typically experience elevated ambient PM_{2.5} concentrations but the evacuated individuals may not be exposed since they leave the area, and (3) because combining them ensured adequate sample size for this exposure category.

Eaton- and Palisades-specific evacuation exposure.

For secondary analyses stratified by fire, we identified evacuation areas associated with each of the two major fires - Eaton and Palisades. Evacuation alerts in the LA County database were linked to specific fires (e.g., Eaton, Palisades). We subset the evacuation polygons to those overlapping a bounding box around each fire's perimeter and assigned census tract exposure accordingly: a tract was considered exposed to Eaton-related evacuation if it overlapped with Eaton-specific polygons, and likewise for Palisades. Census tracts could be exposed to one, both, or neither fire-specific evacuations.

3.6.3 Statistical Analysis.

We modeled healthcare utilization using data from three consecutive November - January periods (2022 - 2025) and predicted health outcomes over a 7-day post-fire period (January 7 - January 13, 2025).

We used a two-stage interrupted time series design that leveraged machine learning methods to estimate the wildfire-attributable change in visit counts following the LA fires. The first stage uses a hybrid Prophet-Extreme Gradient Boosting (XGBoost) model to generate the expected visit rate for each exposure group, encounter type, and outcome combination. For this stage, we use data from November-January 2022-2025 for training and testing, and apply the model to post-wildfire data from January 7-13, 2025. The second stage of this model compares the actual and counterfactual estimates for the post-wildfire period to estimate excess visits for each exposure/encounter/outcome combination.¹⁹

Modeling framework.

We used a Prophet-XGBoost hybrid forecasting approach, described in detail in Dey et al. and Casey et al.^{19,61} Developed to forecast time series data, Prophet is an additive regression model that creates a representation of temporal patterns by decomposing the time series into trend, seasonality, and holiday components:¹⁹

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t \quad (3.1)$$

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where $g(t)$ represents the trend function, $s(t)$ captures periodic seasonal changes, $h(t)$ accounts for holiday effects, and ε_t is the error term. XGBoost complements Prophet by helping identify complex or nuanced relationships and features in the data. XGBoost is a gradient boosting algorithm built on an ensemble of sequential decision trees, with each tree correcting the errors of its predecessors through gradient descent optimization. XGBoost relies on minimizing a regularized objective function to find the optimal tradeoff between error and complexity.¹⁹

By using a hybrid approach, we leverage Prophet's interpretable temporal decomposition while using XGBoost's flexibility to identify patterns in the residuals and additional features. Accordingly, we capture complex nonlinear relationships that cannot be explained by temporal patterns alone (driven by trends, seasonality, and holidays).^{19,61}

Parameterization of models for this analysis.

We separately modeled combinations of exposure category (no smoke, mid-smoke, high smoke, evacuation), encounter type (ED, inpatient), and outcome (all-cause, cardiovascular, injury, neuropsychiatric, and respiratory).

After restricting all models to a daily time series from November-January 2022-2025, we included

covariates for federal holidays, time period, day of week, and month, as well as daily meteorological variables from gridMET (temperature, precipitation, relative humidity, wind velocity, and solar radiation)⁹³ and weekly wastewater surveillance data on influenza, RSV, and SARS-CoV-2 levels.¹²² Time-invariant covariates, such as socioeconomic status, are inherently controlled by the ITS design. Due to differing seasonal patterns, models for respiratory virtual visits were restricted to January 2023 onward.

We used data that ranged from November – January from 2022-2025, omitting the remaining months of the year. Using a time-series split approach, pre-wildfire data were split in time using a cumulative assessment window at the end of the series (duration in days, set in configuration); tuning used rolling time-series cross-validation. Precise split parameters (dates) were updated as needed during model refinement. The split for each model was driven by finding both a clean cutoff period for training/testing (e.g., training data spans November 1, 2022-January 21, 2024 and testing data spans November 1, 2024-January 6, 2025, in order to include balance having sufficient data in both training and testing and work around holidays) based on the data available every year as well as optimizing model performance. In some cases, aberrations in the time series made our standard splitting approach less suitable – leading to slight model-specific deviations. For training, we used a 5-fold cross-validation technique. To balance generalizability with model specificity, we used the same hyperparameter ranges for all models initially, then tailored ranges for specific models to optimize fit on the testing data when the initial fit was poor. We selected the optimal hyperparameter set for each model by minimizing RMSE across folds, and evaluating performance using mean absolute scaled error (MASE), and R^2 . We first selected models with positive R^2 , and then chose the model with the lowest MASE from there. Visual inspections of model fit confirmed all final model selections.

Using the approach described in Dey et al.,⁶¹ we leveraged our best-performing model from the testing period to generate predictions for each exposure/encounter/outcome model across the full study period. Using a Moving Block Bootstrap (MBB) approach, we quantified uncertainty using Monte Carlo simulation across 1,000 iterations. In each iteration, residuals from the pre-event period were segmented into overlapping blocks of length L , resampled with replacement, and recombined into a new residual series that was added back to model-predicted values to construct

a pseudo-time series. The pre-trained model was then reapplied to each pseudo-time series to generate a distribution of post-event predictions. We estimated 95% empirical confidence intervals from these 1,000 iterations, using the 2.5th and 97.5th percentiles as the lower and upper bounds. Excess visit rates were calculated as the difference between observed and predicted rates for each day. We also summed excess visits across the week following wildfire onset. Results are presented as percent of excess visits in the main analysis.

To examine fire-specific effects, we conducted a secondary analysis restricting the evacuation exposure to census tracts affected by the Eaton or Palisades fires separately. We built models to estimate the same measures for each exposure/encounter/outcome combination for each fire using the same methods described above.

3.7 Supplemental figures.

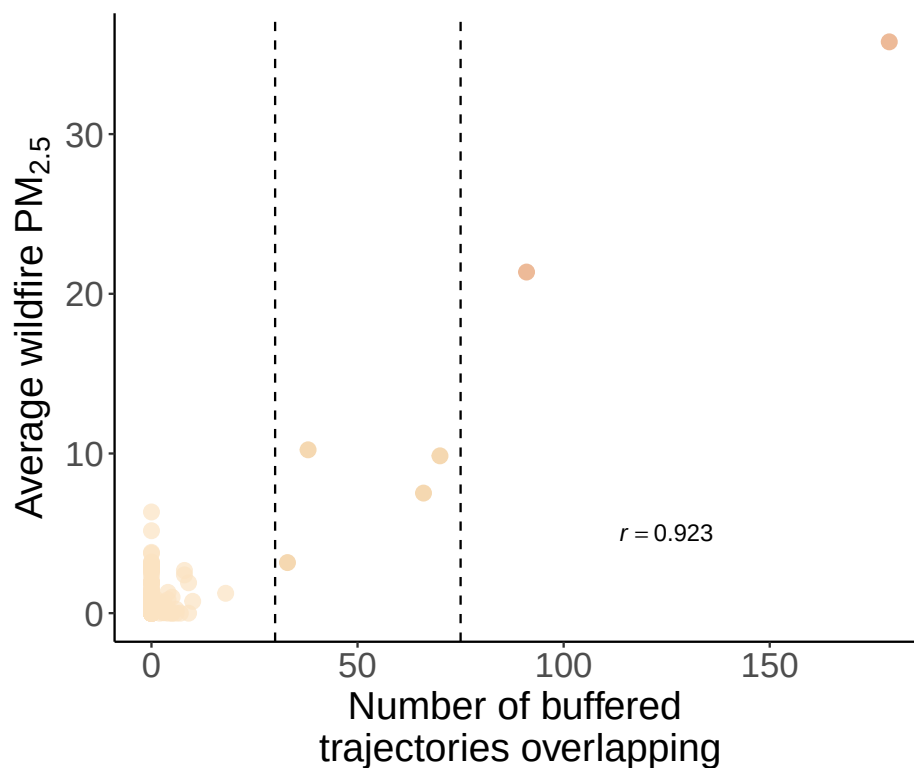


Figure 3.4: Comparison of exposure metric in this study and Environmental Protection Agency Monitoring station wildfire PM_{2.5} estimates. We used the National Oceanic and Atmospheric Administration’s (NOAA) Air Resources Laboratory (ARL) Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model trajectories to estimate wildfire PM_{2.5} exposure. Exposure was determined based on the number of trajectories intersecting a census tract. To assess the validity of these trajectories as an exposure metric, we compared the number of trajectories overlapping each census tract with the average smoke PM_{2.5}. We found that these values were highly correlated. We thus proceeded with our exposure assessment using the trajectories and binned this exposure into (1) minimal smoke exposure, (2) moderate smoke exposure, and (3) high smoke exposure.

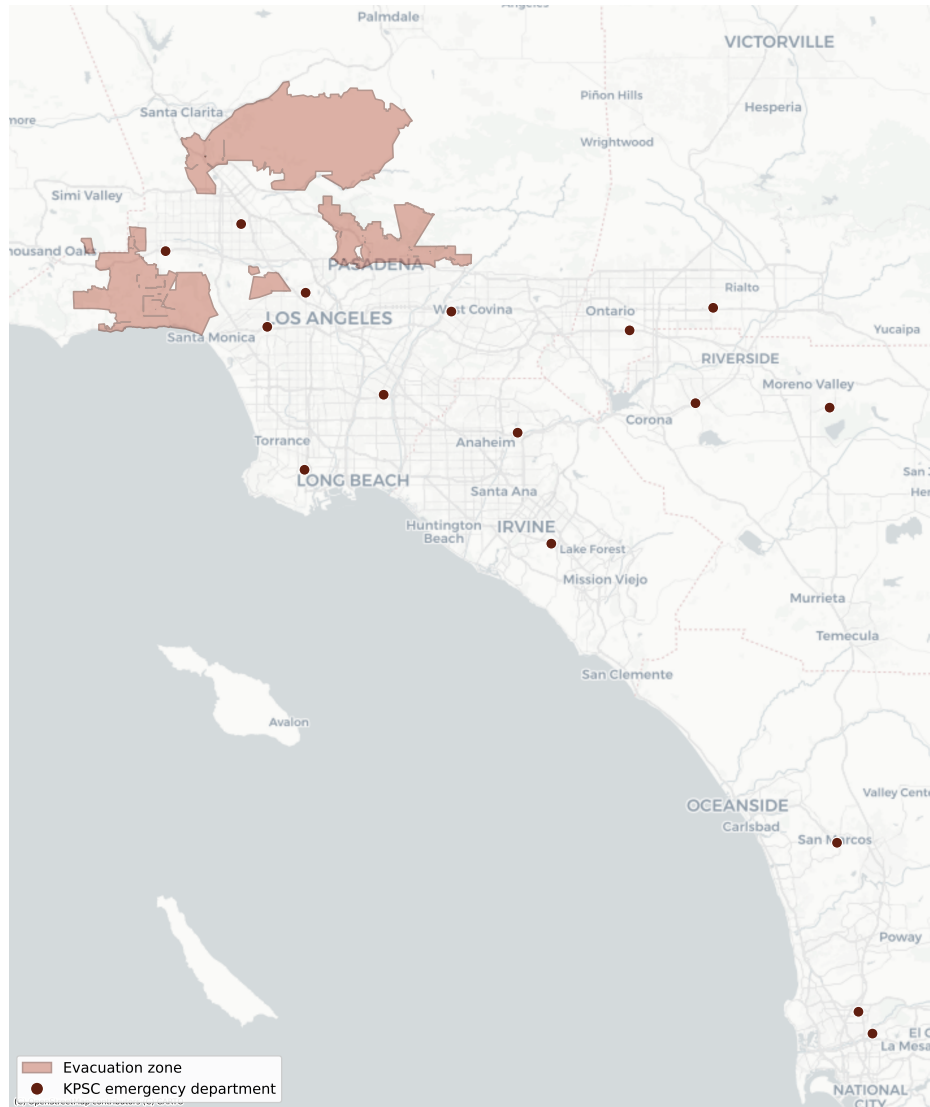


Figure 3.5: Kaiser Permanente Southern California emergency departments and evacuated areas. Kaiser Permanente Southern California (KPSC) emergency departments (ED) and the areas that were evacuated during the 2025 LA fires.

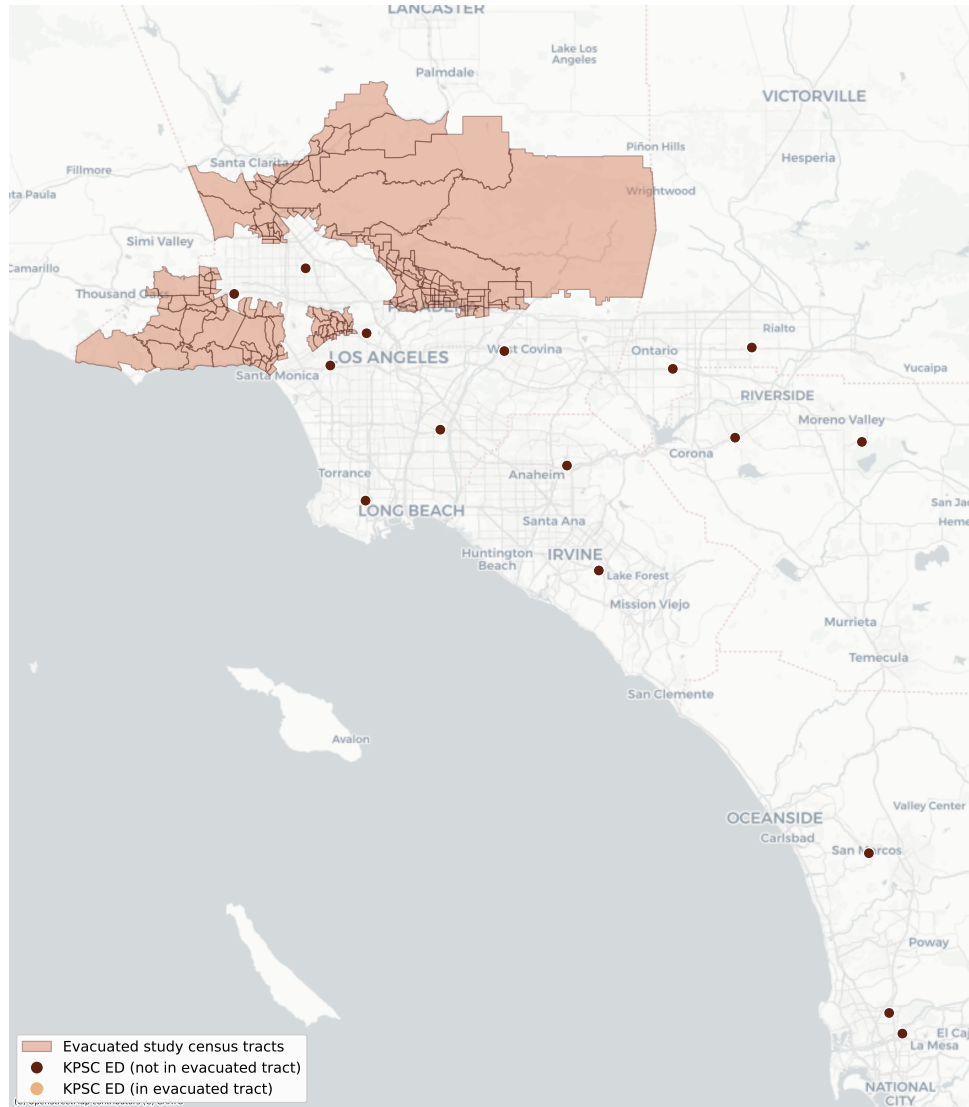


Figure 3.6: Kaiser Permanente Southern California Emergency Departments and evacuated census tracts. Kaiser Permanente Southern California (KPSC) Emergency Departments (ED) and the tracts that were considered were evacuated during the 2025 LA fires for this analysis.

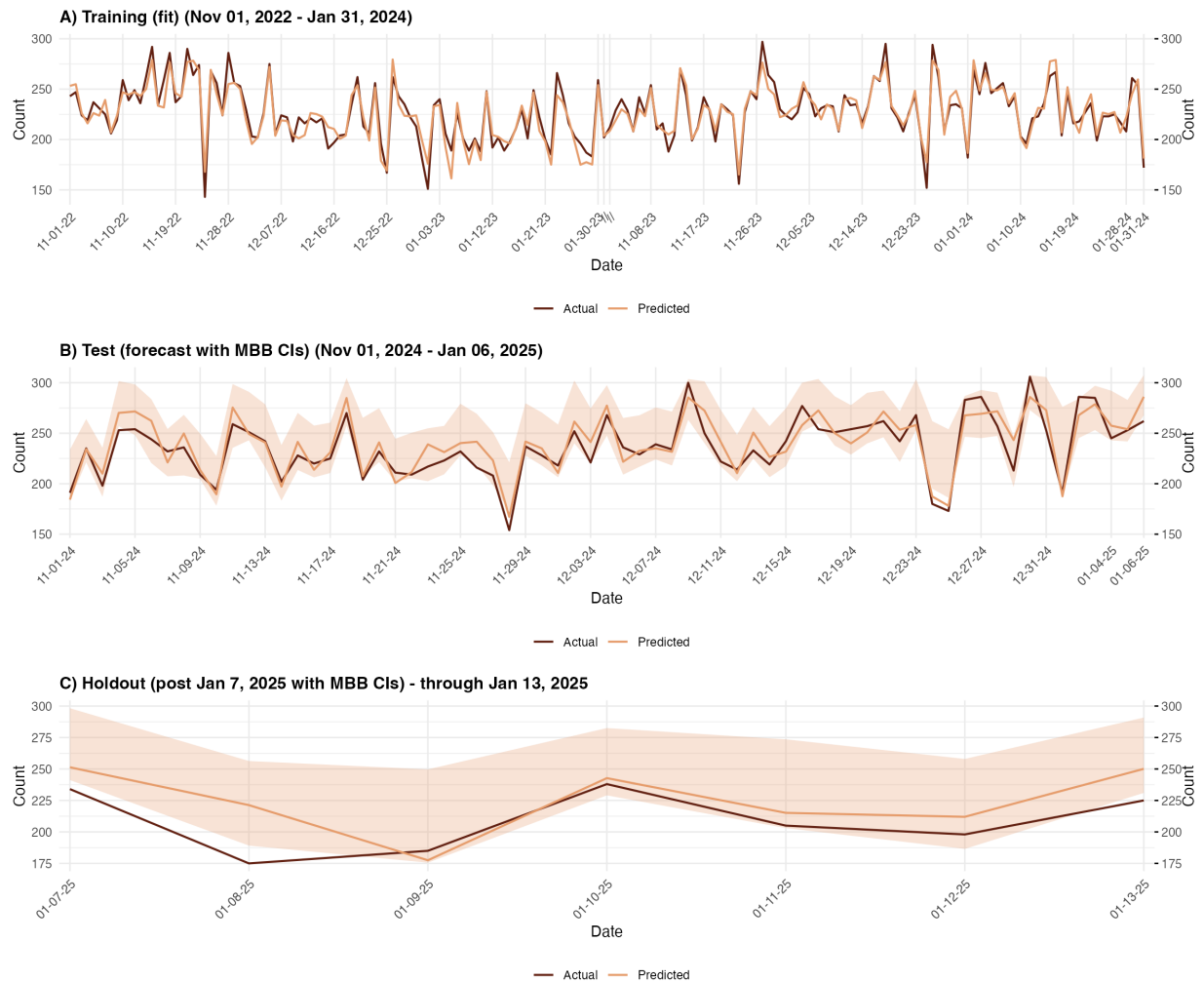


Figure 3.7: Model fit and performance diagnostics. Panel A shows model training performance (November 1, 2022 – January 31, 2024), Panel B shows model performance on testing data (held out from training) (November 1, 2024 – January 6, 2025), and Panel C shows the holdout (post-event) period observed time series and predicted (expected) time series (January 7, 2025 – January 13, 2025). The predicted (expected) values represent the counterfactual time series – what would have been expected in the absence of the fires – accounting for seasonal variation, long-term secular trends, and day-of-week effects that characterize healthcare utilization patterns. Comparing observed values to these expected values isolates the signal attributable to the event. Actual values are shown in dark red; predicted (expected) values in orange; shaded regions represent 95% Moving Block Bootstrap (MBB) confidence intervals (CIs).

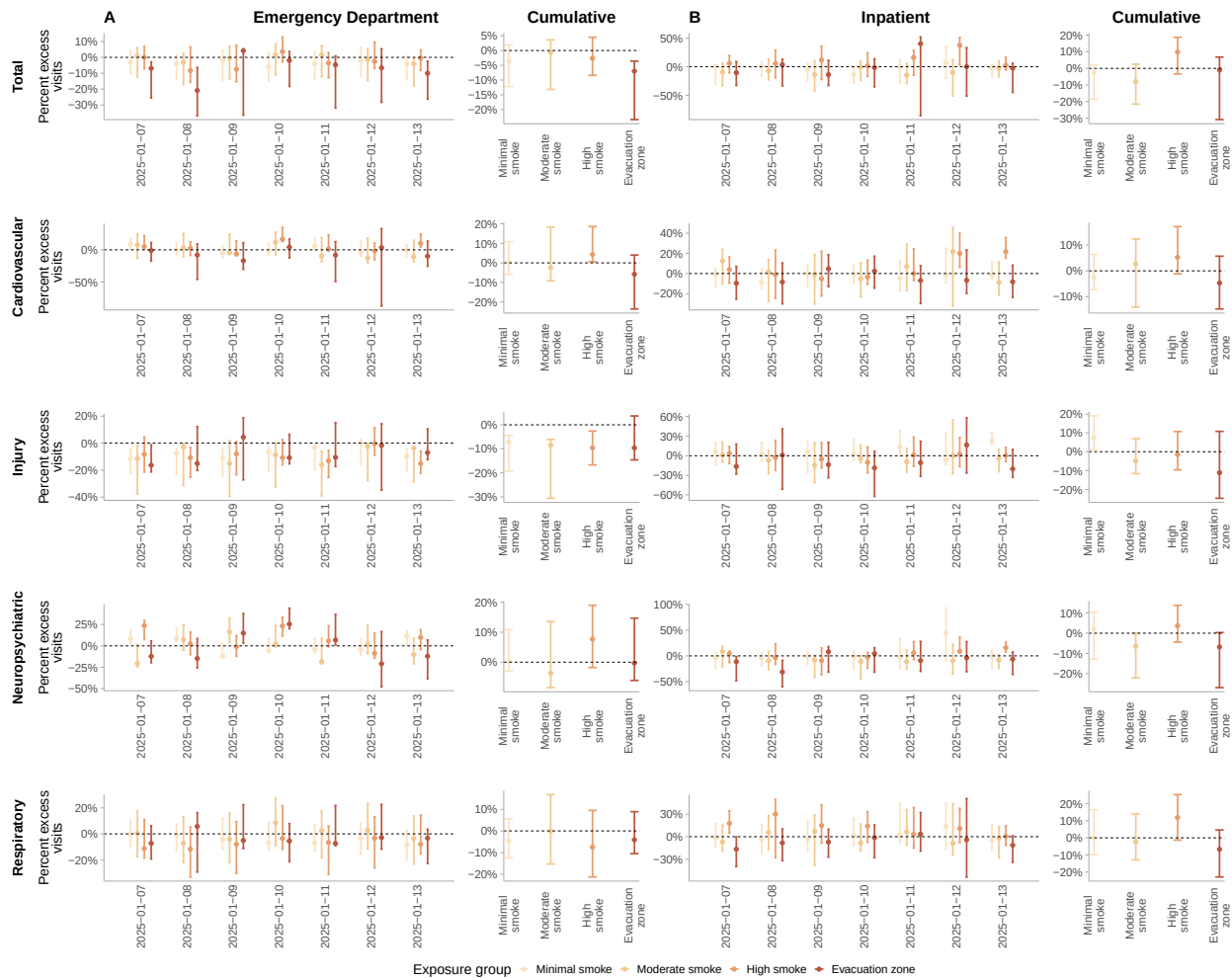


Figure 3.8: Daily cause-specific percent excess emergency department and inpatient visits due to wildfire PM_{2.5} and evacuation. Association between census tract-level (1) no exposure, (2) moderate smoke, (3) high smoke, and (4) evacuation exposure during the 2025 LA fires and percent change in excess all-cause and cause-specific emergency department and inpatient visit rates in the Kaiser Permanente Southern California catchment area from January 7-13, 2025. Cause-specific visits included cardiovascular, injury, neuropsychiatric, and respiratory. Estimates are from an interrupted time-series design that leveraged machine learning methods to estimate the wildfire-attributable change in visit rates following the LA fires. Each encounter type/exposure category/health endpoint was modeled separately using data from November-January 2022-2025 and time-varying covariates to model pre-fire trends. These 40 separate models were then used to predict expected post-LA fire trends. By comparing the post-fire trends predicted from our models, which served as a counterfactual, to observed post-fire trends, we calculated the percent change in excess visit rates attributable to the fires for the 7 days following ignition. 95% empirical confidence intervals were computed using Monte Carlo simulation with 1,000 iterations, using the 2.5th and 97.5th percentiles as the lower and upper bounds.

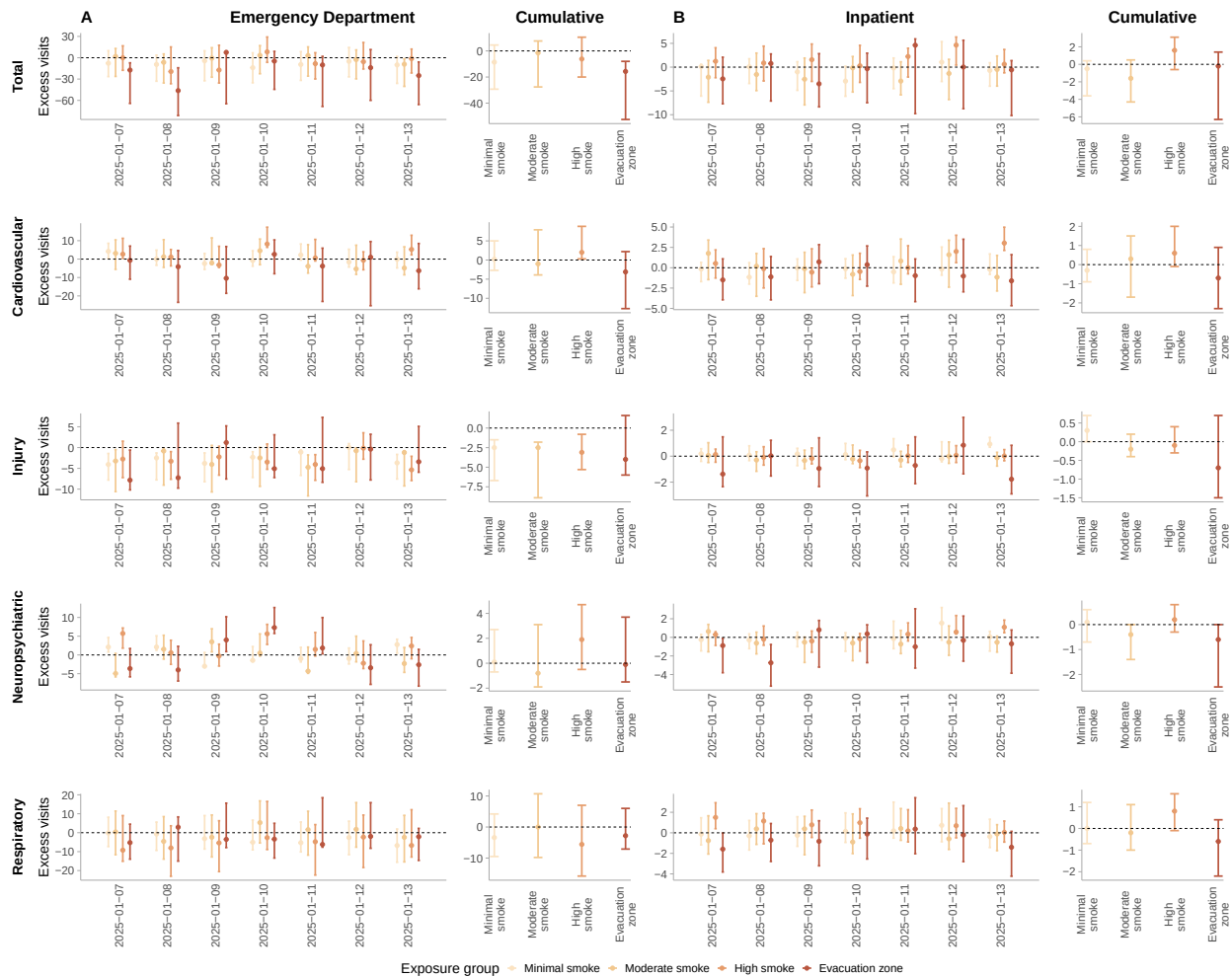


Figure 3.9: Daily cause-specific excess emergency department and inpatient visits due to wildfire PM_{2.5} and evacuation. Association between census tract-level (1) no exposure, (2) moderate smoke, (3) high smoke, and (4) evacuation exposure during the 2025 LA fires and excess all-cause and cause-specific emergency department and inpatient visit rates (per 100,000) in the Kaiser Permanente Southern California catchment area from January 7-13, 2025. Cause-specific visits included cardiovascular, injury, neuropsychiatric, and respiratory. Estimates are from an interrupted time-series design that leveraged machine learning methods to estimate the wildfire-attributable change in visit rates following the LA fires. Each encounter type/exposure category/health endpoint was modeled separately using data from November-January 2022-2025 and time-varying covariates to model pre-fire trends. These 40 separate models were then used to predict expected post-LA fire trends. By comparing the post-fire trends predicted from our models, which served as a counterfactual, to observed post-fire trends, we calculated the excess visit rates attributable to the fires for the 7 days following ignition. 95% empirical confidence intervals were computed using Monte Carlo simulation with 1,000 iterations, using the 2.5th and 97.5th percentiles as the lower and upper bounds.

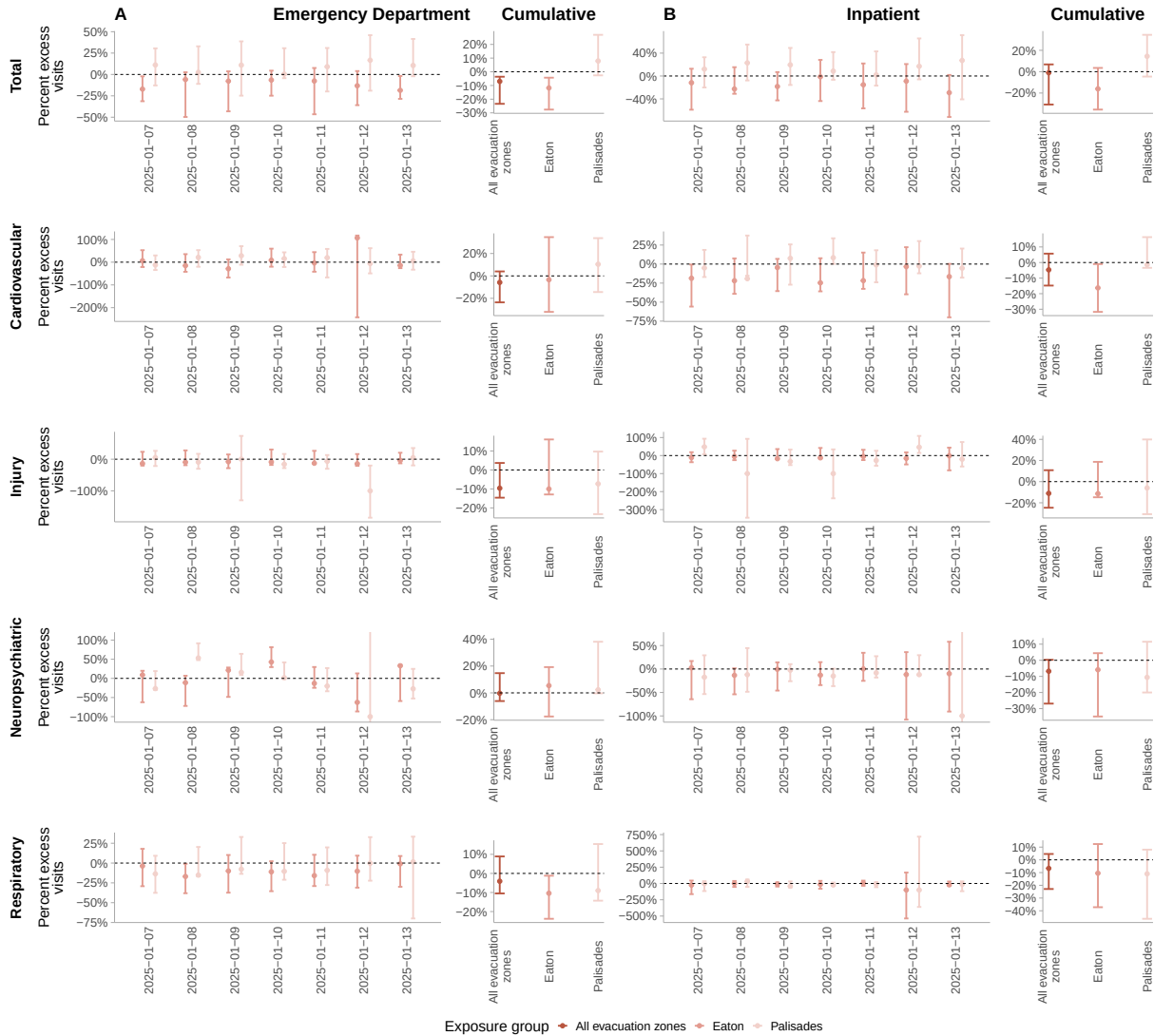


Figure 3.10: Daily cause-specific percent excess emergency department and inpatient visits due to evacuation, by evacuation zone. Association between residing in the Eaton or Palisades evacuation zones during the 2025 LA fires and percent change in excess all-cause and cause-specific emergency department and inpatient visit rates in the Kaiser Permanente Southern California catchment area from January 7-13, 2025. Cause-specific visits included cardiovascular, injury, neuropsychiatric, and respiratory. Estimates are from an interrupted time-series design that leveraged machine learning methods to estimate the wildfire-attributable change in visit rates following the LA fires. Each encounter type/exposure category (Eaton vs. Palisades zone)/health endpoint was modeled separately using data from November-January 2022-2025 and time-varying covariates to model pre-fire trends. These 20 separate models were then used to predict expected post-LA fire trends. By comparing the post-fire trends predicted from our models, which served as a counterfactual, to observed post-fire trends, we calculated the percent change in excess visit rates attributable to the fires for the 7 days following ignition. 95% empirical confidence intervals were computed using Monte Carlo simulation with 1,000 iterations, using the 2.5th and 97.5th percentiles as the lower and upper bounds. When the 95% confidence interval lower or upper limits were more than 100 times larger than the next-most-extreme value, we truncated the y-axis to the second-highest (or second-lowest) limit plus a 20% buffer so that the main effect patterns could be seen.

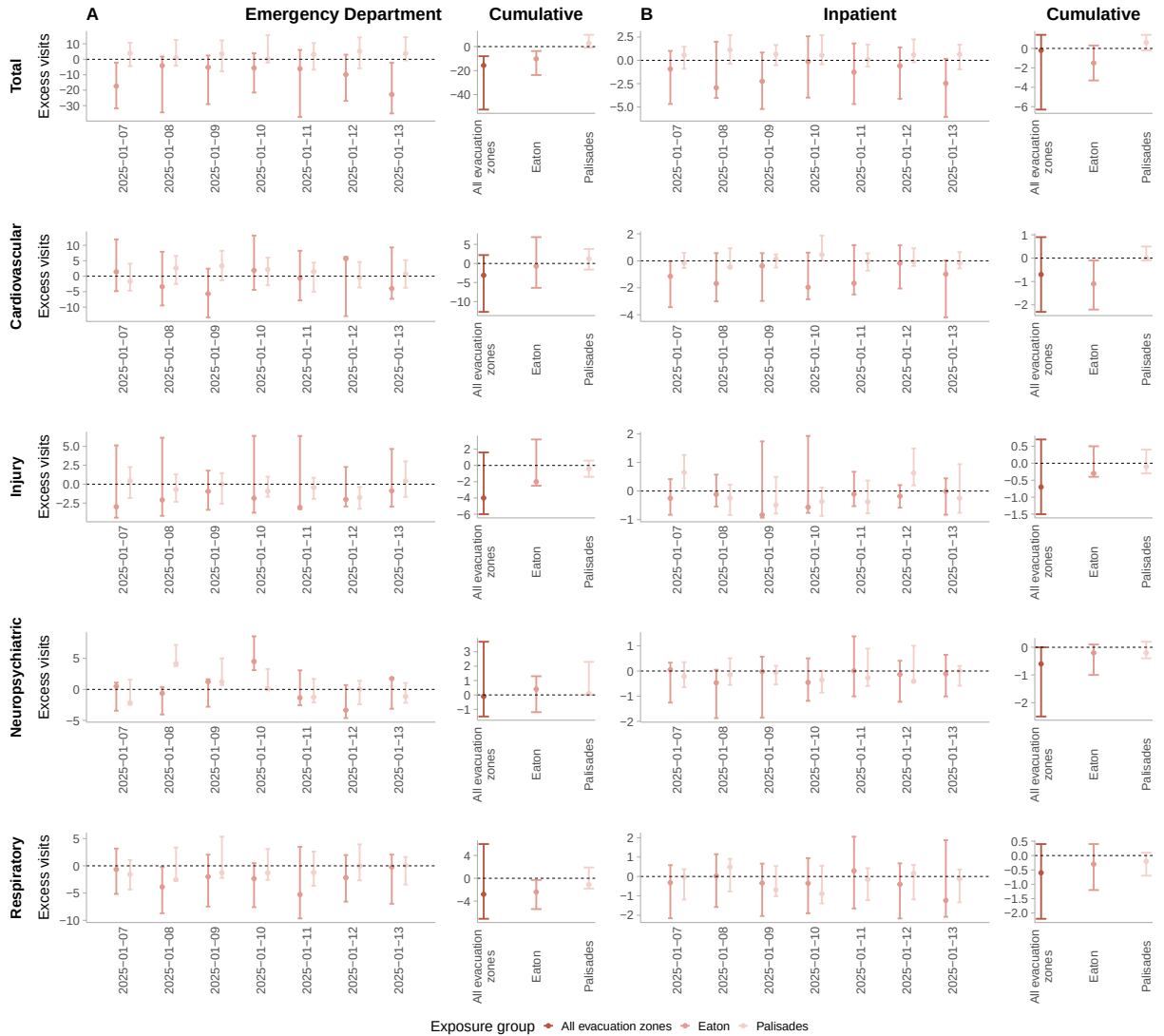


Figure 3.11: Daily cause-specific excess emergency department and inpatient visits due to evacuation, by evacuation zone. Association between residing in the Eaton or Palisades evacuation zones during the 2025 LA fires and excess all-cause and cause-specific emergency department and inpatient visit rates (per 100,000) in the Kaiser Permanente Southern California catchment area from January 7-13, 2025. Cause-specific visits included cardiovascular, injury, neuropsychiatric, and respiratory. Estimates are from an interrupted time-series design that leveraged machine learning methods to estimate the wildfire-attributable change in visit rates following the LA fires. Each encounter type/exposure category (Eaton vs. Palisades zone)/health endpoint was modeled separately using data from November-January 2022-2025 and time-varying covariates to model pre-fire trends. These 20 separate models were then used to predict expected post-LA fire trends. By comparing the post-fire trends predicted from our models, which served as a counterfactual, to observed post-fire trends, we calculated the excess visit rates attributable to the fires for the 7 days following ignition. 95% empirical confidence intervals were computed using Monte Carlo simulation with 1,000 iterations, using the 2.5th and 97.5th percentiles as the lower and upper bounds. When the 95% confidence interval lower or upper limits were more than 100 times larger than the next-most-extreme value, we truncated the y-axis to the second-highest (or second-lowest) limit plus a 20% buffer so that the main effect patterns could be seen.

3.8 Supplemental tables.

	Total (N=63,826)	Eaton (N=44,335)	Palisades (N=19,491)
Age in years, median (IQR)	49 (26, 67)	47 (25, 65)	54 (28, 70)
Sex, n (%)			
Female	33,487 (52.5%)	23,265 (52.5%)	10,222 (52.4%)
Male	30,330 (47.5%)	21,064 (47.5%)	9,266 (47.5%)
Other	2 (<0.1%)	1 (<0.1%)	1 (<0.1%)
Unknown	7 (<0.1%)	5 (<0.1%)	2 (<0.1%)
Race and ethnicity, n (%)			
Hispanic	12,851 (20.1%)	10,784 (24.3%)	2,067 (10.6%)
Non-Hispanic Asian	11,312 (17.7%)	8,614 (19.4%)	2,698 (13.8%)
Non-Hispanic Black	4,314 (6.8%)	3,794 (8.6%)	520 (2.7%)
Non-Hispanic white	29,489 (46.2%)	16,754 (37.8%)	12,735 (65.3%)
Unknown	3,137 (4.9%)	2,433 (5.5%)	704 (3.6%)
Other	2,723 (4.3%)	1,956 (4.4%)	767 (3.9%)

Table 3.2: Demographic characteristics of Kaiser Permanente Southern California patients in the Eaton and Palisades evacuation zones. Number of Kaiser Permanente Southern California patients in the Eaton and Palisades evacuation areas.

<i>Percent Excess (95% CI)</i>					
Date	All-cause	Cardiovascular	Injury	Neuropsychiatric	Respiratory
Jan 07	-6.9 (-25.6, -2.9)	-1.1 (-17.4, 11.3)	-16.4 (-21.3, -1.3)	-12.2 (-19.7, 5.8)	-7.3 (-19.4, 6.2)
Jan 08	-20.9 (-36.7, -6.4)	-8.1 (-46.0, 9.1)	-15.1 (-20.2, 12.2)	-14.8 (-25.8, 8.5)	5.7 (-29.4, 16.3)
Jan 09	4.2 (-36.4, 5.3)	-16.9 (-30.3, 11.1)	4.3 (-27.2, 18.7)	14.8 (3.3, 37.8)	-5.1 (-11.3, 22.4)
Jan 10	-2.0 (-18.3, 3.7)	4.2 (-12.7, 16.7)	-10.8 (-15.3, 6.5)	25.5 (20.0, 44.1)	-5.4 (-21.5, 7.9)
Jan 11	-4.7 (-31.9, 0.9)	-8.1 (-49.1, 12.7)	-10.6 (-17.4, 15.1)	6.8 (1.1, 36.7)	-7.4 (-9.1, 21.9)
Jan 12	-6.6 (-28.3, 5.4)	3.5 (-87.4, 32.9)	-1.7 (-34.8, 14.3)	-20.9 (-47.8, 16.6)	-2.8 (-11.8, 22.7)
Jan 13	-10.0 (-26.3, -2.4)	-10.0 (-25.5, 13.4)	-7.1 (-12.3, 10.5)	-12.1 (-38.4, 6.8)	-3.3 (-22.8, 3.5)
Cumulative	-7.0 (-23.4, -3.6)	-5.8 (-23.6, 4.0)	-9.6 (-14.6, 3.7)	-0.3 (-6.1, 14.7)	-4.1 (-10.5, 8.9)

Table 3.3: Daily cause-specific percent excess emergency department visits due to evacuation. Association between census tract-level evacuation exposure during the 2025 LA fires and percent change in excess all-cause and cause-specific emergency department visit rates in the Kaiser Permanente Southern California catchment area from January 7-13, 2025. Cause-specific visits included cardiovascular, injury, neuropsychiatric, and respiratory. Estimates are from an interrupted time-series design that leveraged machine learning methods to estimate the wildfire-attributable change in visit rates following the LA fires. Each encounter type/exposure category/health endpoint was modeled separately using data from November-January 2022-2025 and time-varying covariates to model pre-fire trends. These 40 separate models were then used to predict expected post-LA fire trends. By comparing the post-fire trends predicted from our models, which served as a counterfactual, to observed post-fire trends, we calculated the percent change in excess visit rates attributable to the fires for the 7 days following ignition. 95% empirical confidence intervals were computed using Monte Carlo simulation with 1,000 iterations, using the 2.5th and 97.5th percentiles as the lower and upper bounds.

<i>Excess Visits (95% CI)</i>					
Date	All-cause	Cardiovascular	Injury	Neuropsychiatric	Respiratory
Jan 07	-17.4 (-64.2, -7.2)	-0.7 (-10.9, 7.1)	-7.8 (-10.2, -0.6)	-3.6 (-5.8, 1.7)	-5.2 (-14.0, 4.5)
Jan 08	-46.3 (-81.3, -14.2)	-4.1 (-23.5, 4.6)	-7.3 (-9.8, 5.9)	-4.0 (-7.0, 2.3)	2.9 (-15.0, 8.3)
Jan 09	7.5 (-64.7, 9.4)	-10.4 (-18.6, 6.8)	1.2 (-7.6, 5.2)	4.0 (0.9, 10.2)	-3.5 (-7.9, 15.6)
Jan 10	-4.7 (-44.5, 8.9)	2.6 (-7.9, 10.4)	-5.1 (-7.2, 3.1)	7.3 (5.7, 12.6)	-3.4 (-13.4, 5.0)
Jan 11	-10.1 (-68.5, 1.9)	-3.8 (-23.0, 5.9)	-5.1 (-8.4, 7.3)	1.9 (0.3, 10.0)	-6.2 (-7.6, 18.5)
Jan 12	-14.0 (-60.0, 11.5)	1.0 (-25.3, 9.5)	-0.4 (-7.8, 3.2)	-3.4 (-7.9, 2.7)	-2.0 (-8.2, 15.9)
Jan 13	-25.1 (-65.8, -6.0)	-6.3 (-16.1, 8.5)	-3.4 (-5.9, 5.1)	-2.6 (-8.3, 1.5)	-2.1 (-14.6, 2.3)
Cumulative	-15.7 (-52.5, -8.0)	-3.1 (-12.7, 2.2)	-4.0 (-6.0, 1.6)	-0.1 (-1.5, 3.7)	-2.8 (-7.1, 6.0)

Table 3.4: Daily cause-specific excess emergency department visits due to evacuation. Association between census tract-level evacuation exposure during the 2025 LA fires and excess all-cause and cause-specific emergency department visit rates (per 100,000) in the Kaiser Permanente Southern California catchment area from January 7-13, 2025. Cause-specific visits included cardiovascular, injury, neuropsychiatric, and respiratory. Estimates are from an interrupted time-series design that leveraged machine learning methods to estimate the wildfire-attributable change in visit rates following the LA fires. Each encounter type/exposure category/health endpoint was modeled separately using data from November-January 2022-2025 and time-varying covariates to model pre-fire trends. These 40 separate models were then used to predict expected post-LA fire trends. By comparing the post-fire trends predicted from our models, which served as a counterfactual, to observed post-fire trends, we calculated the excess visit rates attributable to the fires for the 7 days following ignition. 95% empirical confidence intervals were computed using Monte Carlo simulation with 1,000 iterations, using the 2.5th and 97.5th percentiles as the lower and upper bounds.

Percent Excess (95% CI)					
Date	All-cause	Cardiovascular	Injury	Neuropsychiatric	Respiratory
Jan 07	-17.1 (-31.3, -2.2)	6.3 (-21.4, 52.7)	-13.6 (-20.2, 23.3)	8.9 (-62.4, 19.8)	-3.7 (-29.2, 18.0)
Jan 08	-5.9 (-49.7, 2.6)	-15.1 (-42.3, 35.3)	-9.4 (-19.0, 27.8)	-11.2 (-72.0, 6.8)	-16.9 (-38.0, -0.9)
Jan 09	-7.8 (-43.1, 3.7)	-28.9 (-67.6, 12.4)	-8.0 (-28.3, 15.0)	21.3 (-48.4, 28.4)	-10.0 (-37.4, 10.2)
Jan 10	-6.5 (-24.8, 4.4)	8.5 (-20.0, 59.5)	-8.9 (-18.1, 30.6)	42.8 (29.4, 81.4)	-11.0 (-35.5, 2.3)
Jan 11	-7.6 (-46.6, 7.6)	-3.2 (-42.0, 44.2)	-12.7 (-13.7, 26.5)	-13.0 (-24.7, 29.6)	-15.8 (-29.0, 10.5)
Jan 12	-13.2 (-35.9, 4.0)	106.8 (-242.6, 117.1)	-14.4 (-21.0, 16.2)	-62.6 (-86.4, 13.0)	-10.3 (-31.0, 9.3)
Jan 13	-18.6 (-28.5, -1.9)	-14.2 (-26.2, 33.2)	-3.8 (-13.0, 20.4)	32.9 (-59.2, 35.6)	-1.0 (-29.9, 8.9)
Cumulative	-11.8 (-27.6, -4.3)	-3.4 (-32.1, 34.6)	-10.0 (-12.9, 16.1)	5.4 (-17.6, 19.2)	-10.4 (-23.8, -1.2)

Table 3.5: Daily cause-specific percent excess emergency department visits due to evacuation in the Eaton zone. Association between residing in the Eaton evacuation zone during the 2025 LA fires and percent change in excess all-cause and cause-specific emergency department visit rates in the Kaiser Permanente Southern California catchment area from January 7-13, 2025. Cause-specific visits included cardiovascular, injury, neuropsychiatric, and respiratory. Estimates are from an interrupted time-series design that leveraged machine learning methods to estimate the wildfire-attributable change in visit rates following the LA fires. Each encounter type/exposure category/health endpoint was modeled separately using data from November-January 2022-2025 and time-varying covariates to model pre-fire trends. These 40 separate models were then used to predict expected post-LA fire trends. By comparing the post-fire trends predicted from our models, which served as a counterfactual, to observed post-fire trends, we calculated the percent change in excess visit rates attributable to the fires for the 7 days following ignition. 95% empirical confidence intervals were computed using Monte Carlo simulation with 1,000 iterations, using the 2.5th and 97.5th percentiles as the lower and upper bounds.

Excess Visits (95% CI)					
Date	All-cause	Cardiovascular	Injury	Neuropsychiatric	Respiratory
Jan 07	-17.4 (-31.7, -2.2)	1.4 (-4.8, 11.9)	-3.0 (-4.4, 5.1)	0.5 (-3.4, 1.1)	-0.7 (-5.2, 3.2)
Jan 08	-4.1 (-34.4, 1.8)	-3.4 (-9.5, 7.9)	-2.1 (-4.2, 6.1)	-0.6 (-4.1, 0.4)	-3.9 (-8.7, -0.2)
Jan 09	-5.2 (-29.0, 2.5)	-5.7 (-13.3, 2.4)	-1.0 (-3.4, 1.8)	1.2 (-2.8, 1.6)	-2.0 (-7.5, 2.0)
Jan 10	-5.6 (-21.5, 3.8)	1.9 (-4.4, 13.1)	-1.9 (-3.8, 6.4)	4.5 (3.1, 8.6)	-2.4 (-7.6, 0.5)
Jan 11	-6.1 (-37.3, 6.1)	-0.6 (-7.8, 8.2)	-3.1 (-3.3, 6.4)	-1.3 (-2.6, 3.1)	-5.3 (-9.7, 3.5)
Jan 12	-9.9 (-26.9, 3.0)	5.7 (-12.9, 6.2)	-2.0 (-2.9, 2.3)	-3.3 (-4.6, 0.7)	-2.2 (-6.6, 2.0)
Jan 13	-22.8 (-35.0, -2.3)	-4.0 (-7.3, 9.3)	-0.9 (-3.0, 4.7)	1.7 (-3.1, 1.9)	-0.2 (-7.0, 2.1)
Cumulative	-10.2 (-23.7, -3.7)	-0.7 (-6.4, 6.9)	-2.0 (-2.5, 3.2)	0.4 (-1.2, 1.3)	-2.4 (-5.4, -0.3)

Table 3.6: Daily cause-specific excess emergency department visits due to evacuation in the Eaton zone. Association between residing in the Eaton evacuation zone during the 2025 LA fires and excess all-cause and cause-specific emergency department visit rates (per 100,000) in the Kaiser Permanente Southern California catchment area from January 7-13, 2025. Cause-specific visits included cardiovascular, injury, neuropsychiatric, and respiratory. Estimates are from an interrupted time-series design that leveraged machine learning methods to estimate the wildfire-attributable change in visit rates following the LA fires. Each encounter type/exposure category/health endpoint was modeled separately using data from November-January 2022-2025 and time-varying covariates to model pre-fire trends. These 40 separate models were then used to predict expected post-LA fire trends. By comparing the post-fire trends predicted from our models, which served as a counterfactual, to observed post-fire trends, we calculated the excess visit rates attributable to the fires for the 7 days following ignition. 95% empirical confidence intervals were computed using Monte Carlo simulation with 1,000 iterations, using the 2.5th and 97.5th percentiles as the lower and upper bounds.

Percent Excess (95% CI)					
Date	All-cause	Cardiovascular	Injury	Neuropsychiatric	Respiratory
Jan 07	11.1 (-12.9, 30.5)	-12.3 (-34.3, 29.7)	5.2 (-21.5, 26.4)	-26.7 (-30.2, 19.0)	-13.6 (-37.5, 9.2)
Jan 08	2.4 (-11.0, 32.9)	21.1 (-20.2, 53.0)	-9.1 (-30.3, 16.9)	53.2 (47.8, 91.6)	-15.2 (-16.7, 20.3)
Jan 09	10.9 (-24.8, 38.7)	28.4 (-11.2, 70.3)	0.2 (-129.8, 73.5)	15.6 (8.9, 64.1)	-7.7 (-13.6, 32.9)
Jan 10	0.4 (-4.3, 30.7)	15.6 (-21.3, 43.3)	-15.9 (-28.0, 16.5)	1.8 (-1.8, 41.7)	-10.4 (-21.0, 25.2)
Jan 11	9.0 (-19.9, 30.9)	19.7 (-67.2, 58.3)	-6.7 (-30.3, 13.1)	-20.1 (-33.7, 26.9)	-9.2 (-27.7, 19.8)
Jan 12	16.6 (-19.0, 45.9)	-5.9 (-49.4, 61.6)	-100.0 (-184.8, -20.1)	-100.0 (-9651.7, 16687.0)	-0.2 (-22.3, 32.7)
Jan 13	10.5 (-2.1, 41.5)	5.7 (-33.0, 45.8)	4.9 (-19.6, 35.2)	-27.3 (-52.6, 24.8)	1.5 (-69.9, 33.3)
Cumulative	7.9 (-2.6, 27.0)	10.4 (-14.4, 33.7)	-7.3 (-23.3, 9.7)	2.3 (-0.3, 38.1)	-9.0 (-14.3, 15.4)

Table 3.7: Daily cause-specific percent excess emergency department visits due to evacuation in the Palisades zone. Association between residing in the Palisades evacuation zone during the 2025 LA fires and percent change in excess all-cause and cause-specific emergency department visit rates in the Kaiser Permanente Southern California catchment area from January 7-13, 2025. Cause-specific visits included cardiovascular, injury, neuropsychiatric, and respiratory. Estimates are from an interrupted time-series design that leveraged machine learning methods to estimate the wildfire-attributable change in visit rates following the LA fires. Each encounter type-/exposure category/health endpoint was modeled separately using data from November-January 2022-2025 and time-varying covariates to model pre-fire trends. These 40 separate models were then used to predict expected post-LA fire trends. By comparing the post-fire trends predicted from our models, which served as a counterfactual, to observed post-fire trends, we calculated the percent change in excess visit rates attributable to the fires for the 7 days following ignition. 95% empirical confidence intervals were computed using Monte Carlo simulation with 1,000 iterations, using the 2.5th and 97.5th percentiles as the lower and upper bounds.

<i>Excess Visits (95% CI)</i>					
Date	All-cause	Cardiovascular	Injury	Neuropsychiatric	Respiratory
Jan 07	3.9 (-4.5, 10.7)	-1.7 (-4.7, 4.1)	0.4 (-1.8, 2.3)	-2.2 (-2.5, 1.6)	-1.6 (-4.3, 1.1)
Jan 08	0.9 (-4.2, 12.5)	2.6 (-2.5, 6.6)	-0.7 (-2.3, 1.3)	4.2 (3.7, 7.2)	-2.5 (-2.8, 3.4)
Jan 09	3.4 (-7.8, 12.2)	3.3 (-1.3, 8.2)	0.0 (-2.6, 1.5)	1.2 (0.7, 5.0)	-1.3 (-2.2, 5.4)
Jan 10	0.2 (-2.2, 15.6)	2.2 (-3.0, 6.0)	-0.9 (-1.7, 1.0)	0.1 (-0.1, 3.3)	-1.3 (-2.6, 3.1)
Jan 11	3.1 (-6.8, 10.5)	1.5 (-5.1, 4.4)	-0.4 (-1.9, 0.8)	-1.3 (-2.1, 1.7)	-1.2 (-3.7, 2.6)
Jan 12	5.1 (-5.9, 14.2)	-0.4 (-3.7, 4.6)	-1.8 (-3.3, -0.4)	0.0 (-2.4, 1.4)	-0.0 (-2.7, 3.9)
Jan 13	3.6 (-0.7, 14.3)	0.6 (-3.7, 5.2)	0.4 (-1.7, 3.0)	-1.1 (-2.2, 1.0)	0.1 (-3.4, 1.6)
Cumulative	2.9 (-1.0, 9.8)	1.2 (-1.6, 3.8)	-0.4 (-1.4, 0.6)	0.1 (-0.0, 2.3)	-1.1 (-1.8, 1.9)

Table 3.8: Daily cause-specific excess emergency department visits due to evacuation in the Palisades zone. Association between residing in the Palisades evacuation zone during the 2025 LA fires and excess all-cause and cause-specific emergency department visit rates (per 100,000) in the Kaiser Permanente Southern California catchment area from January 7-13, 2025. Cause-specific visits included cardiovascular, injury, neuropsychiatric, and respiratory. Estimates are from an interrupted time-series design that leveraged machine learning methods to estimate the wildfire-attributable change in visit rates following the LA fires. Each encounter type/exposure category/health endpoint was modeled separately using data from November-January 2022-2025 and time-varying covariates to model pre-fire trends. These 40 separate models were then used to predict expected post-LA fire trends. By comparing the post-fire trends predicted from our models, which served as a counterfactual, to observed post-fire trends, we calculated the excess visit rates attributable to the fires for the 7 days following ignition. 95% empirical confidence intervals were computed using Monte Carlo simulation with 1,000 iterations, using the 2.5th and 97.5th percentiles as the lower and upper bounds.

Percent Excess (95% CI)					
Date	All-cause	Cardiovascular	Injury	Neuropsychiatric	Respiratory
Jan 07	-0.0 (-7.2, 6.8)	5.2 (0.8, 22.0)	-8.2 (-21.4, 4.5)	23.6 (7.5, 29.6)	-11.4 (-18.6, 11.1)
Jan 08	-8.4 (-15.7, 6.5)	2.6 (-8.8, 12.4)	-10.9 (-25.2, -3.2)	2.4 (-10.2, 16.0)	-11.7 (-33.3, 5.3)
Jan 09	-7.5 (-15.4, 7.6)	-6.3 (-9.0, 13.9)	-7.9 (-23.5, 1.1)	-1.1 (-12.2, 11.8)	-8.0 (-30.5, 9.3)
Jan 10	3.6 (-2.9, 12.8)	16.4 (12.8, 34.8)	-10.7 (-16.1, 2.6)	23.2 (11.5, 33.5)	-3.5 (-11.7, 21.8)
Jan 11	-3.6 (-12.9, 3.0)	1.4 (-2.2, 23.1)	-13.1 (-25.4, -5.5)	5.8 (-1.1, 23.5)	-6.7 (-31.2, 6.0)
Jan 12	-2.5 (-7.0, 9.5)	-1.7 (-15.4, 10.5)	-0.5 (-9.0, 11.4)	-8.8 (-14.4, 14.8)	-3.3 (-26.1, 13.2)
Jan 13	-0.5 (-8.2, 4.7)	10.0 (4.4, 24.5)	-15.2 (-22.4, -6.0)	9.7 (-4.1, 19.0)	-8.0 (-15.3, 14.5)
Cumulative	-2.6 (-8.4, 4.5)	4.3 (0.6, 18.6)	-9.6 (-16.7, -2.6)	7.7 (-1.8, 19.0)	-7.5 (-21.3, 9.5)

Table 3.9: Daily cause-specific percent excess emergency department visits due to high smoke. Association between census tract-level high smoke exposure during the 2025 LA fires and percent change in excess all-cause and cause-specific emergency department visit rates in the Kaiser Permanente Southern California catchment area from January 7-13, 2025. Cause-specific visits included cardiovascular, injury, neuropsychiatric, and respiratory. Estimates are from an interrupted time-series design that leveraged machine learning methods to estimate the wildfire-attributable change in visit rates following the LA fires. Each encounter type/exposure category/health endpoint was modeled separately using data from November-January 2022-2025 and time-varying covariates to model pre-fire trends. These 40 separate models were then used to predict expected post-LA fire trends. By comparing the post-fire trends predicted from our models, which served as a counterfactual, to observed post-fire trends, we calculated the percent change in excess visit rates attributable to the fires for the 7 days following ignition. 95% empirical confidence intervals were computed using Monte Carlo simulation with 1,000 iterations, using the 2.5th and 97.5th percentiles as the lower and upper bounds.

<i>Excess Visits (95% CI)</i>					
Date	All-cause	Cardiovascular	Injury	Neuropsychiatric	Respiratory
Jan 07	-0.0 (-17.7, 16.7)	2.7 (0.4, 11.3)	-2.8 (-7.2, 1.5)	5.7 (1.8, 7.2)	-9.2 (-15.1, 9.0)
Jan 08	-19.4 (-36.6, 15.1)	1.1 (-3.7, 5.2)	-3.3 (-7.6, -1.0)	0.6 (-2.5, 3.9)	-8.0 (-23.0, 3.6)
Jan 09	-17.3 (-35.5, 17.5)	-3.2 (-4.5, 7.0)	-2.2 (-6.6, 0.3)	-0.3 (-3.0, 2.9)	-5.4 (-20.5, 6.3)
Jan 10	8.2 (-6.5, 29.1)	8.2 (6.4, 17.3)	-3.5 (-5.2, 0.9)	5.6 (2.8, 8.2)	-2.6 (-8.9, 16.5)
Jan 11	-8.4 (-29.9, 7.0)	0.6 (-1.0, 10.7)	-4.1 (-7.9, -1.7)	1.5 (-0.3, 6.0)	-4.8 (-22.4, 4.3)
Jan 12	-5.6 (-15.9, 21.4)	-0.6 (-5.8, 3.9)	-0.2 (-2.8, 3.6)	-2.2 (-3.6, 3.7)	-2.3 (-18.4, 9.3)
Jan 13	-1.3 (-21.4, 12.1)	5.3 (2.3, 12.9)	-5.4 (-7.9, -2.1)	2.4 (-1.0, 4.7)	-6.7 (-12.8, 12.1)
Cumulative	-6.2 (-20.0, 10.5)	2.0 (0.3, 8.8)	-3.1 (-5.3, -0.8)	1.9 (-0.5, 4.7)	-5.6 (-15.8, 7.0)

Table 3.10: Daily cause-specific excess emergency department visits due to high smoke. Association between census tract-level high smoke exposure during the 2025 LA fires and excess all-cause and cause-specific emergency department visit rates (per 100,000) in the Kaiser Permanente Southern California catchment area from January 7-13, 2025. Cause-specific visits included cardiovascular, injury, neuropsychiatric, and respiratory. Estimates are from an interrupted time-series design that leveraged machine learning methods to estimate the wildfire-attributable change in visit rates following the LA fires. Each encounter type/exposure category/health endpoint was modeled separately using data from November-January 2022-2025 and time-varying covariates to model pre-fire trends. These 40 separate models were then used to predict expected post-LA fire trends. By comparing the post-fire trends predicted from our models, which served as a counterfactual, to observed post-fire trends, we calculated the excess visit rates attributable to the fires for the 7 days following ignition. 95% empirical confidence intervals were computed using Monte Carlo simulation with 1,000 iterations, using the 2.5th and 97.5th percentiles as the lower and upper bounds.

Percent Excess (95% CI)					
Date	All-cause	Cardiovascular	Injury	Neuropsychiatric	Respiratory
Jan 07	0.8 (-12.3, 6.1)	7.5 (-13.3, 25.0)	-11.5 (-37.5, -1.8)	-20.7 (-24.4, 1.7)	0.7 (-17.7, 17.4)
Jan 08	-3.1 (-17.1, 2.5)	2.9 (-10.8, 25.2)	-2.9 (-31.3, -0.3)	7.1 (-5.2, 24.4)	-7.2 (-21.9, 13.3)
Jan 09	-0.3 (-13.6, 7.0)	-4.5 (-5.6, 24.5)	-15.0 (-39.5, 1.9)	16.3 (3.8, 32.5)	-4.1 (-21.9, 16.0)
Jan 10	1.6 (-11.1, 8.4)	11.5 (-7.7, 27.6)	-8.7 (-32.8, 0.2)	2.1 (-1.2, 23.9)	8.6 (-8.8, 27.2)
Jan 11	1.4 (-12.3, 7.3)	-9.5 (-18.6, 19.1)	-15.9 (-39.1, -6.0)	-18.5 (-21.0, 9.0)	2.5 (-18.4, 17.6)
Jan 12	-1.3 (-14.6, 5.4)	-12.9 (-20.1, 18.3)	-2.6 (-27.6, -0.3)	2.0 (-8.9, 24.3)	2.6 (-11.4, 23.6)
Jan 13	-4.1 (-18.1, -0.7)	-10.6 (-18.6, 14.6)	-3.7 (-28.7, -2.4)	-10.3 (-20.9, 8.9)	-3.7 (-23.2, 13.8)
Cumulative	-0.7 (-13.2, 3.6)	-2.4 (-9.2, 18.4)	-8.5 (-30.6, -6.1)	-3.6 (-8.5, 13.6)	-0.1 (-15.3, 16.8)

Table 3.11: Daily cause-specific percent excess emergency department visits due to moderate smoke. Association between census tract-level moderate smoke exposure during the 2025 LA fires and percent change in excess all-cause and cause-specific emergency department visit rates in the Kaiser Permanente Southern California catchment area from January 7-13, 2025. Cause-specific visits included cardiovascular, injury, neuropsychiatric, and respiratory. Estimates are from an interrupted time-series design that leveraged machine learning methods to estimate the wildfire-attributable change in visit rates following the LA fires. Each encounter type/exposure category/health endpoint was modeled separately using data from November-January 2022-2025 and time-varying covariates to model pre-fire trends. These 40 separate models were then used to predict expected post-LA fire trends. By comparing the post-fire trends predicted from our models, which served as a counterfactual, to observed post-fire trends, we calculated the percent change in excess visit rates attributable to the fires for the 7 days following ignition. 95% empirical confidence intervals were computed using Monte Carlo simulation with 1,000 iterations, using the 2.5th and 97.5th percentiles as the lower and upper bounds.

<i>Excess Visits (95% CI)</i>					
Date	All-cause	Cardiovascular	Injury	Neuropsychiatric	Respiratory
Jan 07	1.8 (-26.3, 13.0)	3.1 (-5.6, 10.4)	-3.2 (-10.6, -0.5)	-4.9 (-5.8, 0.4)	0.4 (-11.6, 11.4)
Jan 08	-6.4 (-35.5, 5.3)	1.2 (-4.5, 10.5)	-0.8 (-9.0, -0.1)	1.5 (-1.1, 5.2)	-4.6 (-13.9, 8.5)
Jan 09	-0.6 (-27.3, 14.1)	-2.1 (-2.7, 11.5)	-4.1 (-10.7, 0.5)	3.5 (0.8, 7.0)	-2.4 (-12.8, 9.3)
Jan 10	3.3 (-22.5, 17.0)	4.5 (-3.0, 10.9)	-2.5 (-9.3, 0.1)	0.5 (-0.3, 5.6)	5.3 (-5.4, 16.8)
Jan 11	3.0 (-25.8, 15.2)	-3.9 (-7.6, 7.8)	-4.7 (-11.6, -1.8)	-4.3 (-4.9, 2.1)	1.6 (-11.8, 11.3)
Jan 12	-2.6 (-29.7, 11.0)	-5.3 (-8.3, 7.5)	-0.8 (-8.2, -0.1)	0.4 (-1.8, 5.0)	1.8 (-7.6, 15.9)
Jan 13	-9.1 (-40.3, -1.5)	-4.9 (-8.5, 6.7)	-1.2 (-9.2, -0.8)	-2.3 (-4.7, 2.0)	-2.4 (-15.4, 9.1)
Cumulative	-1.5 (-27.6, 7.6)	-1.0 (-3.9, 7.9)	-2.5 (-8.9, -1.8)	-0.8 (-1.9, 3.1)	-0.0 (-9.8, 10.7)

Table 3.12: Daily cause-specific excess emergency department visits due to moderate smoke. Association between census tract-level moderate smoke exposure during the 2025 LA fires and excess all-cause and cause-specific emergency department visit rates (per 100,000) in the Kaiser Permanente Southern California catchment area from January 7-13, 2025. Cause-specific visits included cardiovascular, injury, neuropsychiatric, and respiratory. Estimates are from an interrupted time-series design that leveraged machine learning methods to estimate the wildfire-attributable change in visit rates following the LA fires. Each encounter type/exposure category/health endpoint was modeled separately using data from November-January 2022-2025 and time-varying covariates to model pre-fire trends. These 40 separate models were then used to predict expected post-LA fire trends. By comparing the post-fire trends predicted from our models, which served as a counterfactual, to observed post-fire trends, we calculated the excess visit rates attributable to the fires for the 7 days following ignition. 95% empirical confidence intervals were computed using Monte Carlo simulation with 1,000 iterations, using the 2.5th and 97.5th percentiles as the lower and upper bounds.

<i>Percent Excess (95% CI)</i>					
Date	All-cause	Cardiovascular	Injury	Neuropsychiatric	Respiratory
Jan 07	-10.5 (-32.8, 8.9)	-9.7 (-25.4, 7.0)	-16.5 (-28.1, 17.7)	-11.2 (-48.3, -1.4)	-16.6 (-39.8, -0.3)
Jan 08	3.6 (-33.5, 13.0)	-8.5 (-30.1, 10.5)	1.0 (-51.4, 41.2)	-31.3 (-60.0, -8.8)	-8.2 (-32.0, 10.4)
Jan 09	-13.8 (-32.7, 11.1)	4.7 (-12.8, 18.6)	-13.7 (-33.7, 20.4)	7.9 (-31.5, 17.8)	-7.0 (-27.2, 9.9)
Jan 10	-1.6 (-35.1, 13.8)	2.4 (-14.5, 17.2)	-18.7 (-62.3, 6.7)	4.4 (-31.6, 15.7)	-1.3 (-28.0, 15.7)
Jan 11	40.5 (-85.7, 52.0)	-7.0 (-29.8, 7.7)	-10.7 (-31.5, 22.1)	-9.2 (-30.0, 27.9)	3.5 (-19.1, 32.1)
Jan 12	0.1 (-51.5, 33.3)	-6.8 (-19.7, 23.3)	16.4 (-26.4, 58.0)	-3.8 (-30.8, 27.5)	-4.0 (-53.8, 50.8)
Jan 13	-2.5 (-45.1, 6.1)	-8.2 (-23.8, 8.2)	-20.2 (-33.1, 9.5)	-6.5 (-36.1, 7.4)	-11.3 (-34.1, 1.1)
Cumulative	-1.0 (-30.8, 6.8)	-4.7 (-14.8, 5.7)	-11.1 (-24.7, 10.8)	-6.8 (-26.9, 0.3)	-6.7 (-22.9, 4.6)

Table 3.13: Daily cause-specific percent excess inpatient visits due to evacuation. Association between census tract-level evacuation exposure during the 2025 LA fires and percent change in excess all-cause and cause-specific inpatient admission rates (per 100,000) in the Kaiser Permanente Southern California catchment area from January 7-13, 2025. Cause-specific visits included cardiovascular, injury, neuropsychiatric, and respiratory. Estimates are from an interrupted time-series design that leveraged machine learning methods to estimate the wildfire-attributable change in visit rates following the LA fires. Each encounter type/exposure category/health endpoint was modeled separately using data from November-January 2022-2025 and time-varying covariates to model pre-fire trends. These 40 separate models were then used to predict expected post-LA fire trends. By comparing the post-fire trends predicted from our models, which served as a counterfactual, to observed post-fire trends, we calculated the percent change in excess visit rates attributable to the fires for the 7 days following ignition. 95% empirical confidence intervals were computed using Monte Carlo simulation with 1,000 iterations, using the 2.5th and 97.5th percentiles as the lower and upper bounds.

<i>Excess Visits (95% CI)</i>					
Date	All-cause	Cardiovascular	Injury	Neuropsychiatric	Respiratory
Jan 07	-2.5 (-7.7, 2.1)	-1.5 (-3.9, 1.1)	-1.4 (-2.4, 1.5)	-0.9 (-3.8, -0.1)	-1.6 (-3.8, -0.0)
Jan 08	0.8 (-7.1, 2.8)	-1.1 (-3.9, 1.4)	0.0 (-1.5, 1.2)	-2.7 (-5.2, -0.8)	-0.7 (-2.8, 0.9)
Jan 09	-3.5 (-8.3, 2.8)	0.7 (-2.0, 2.8)	-0.9 (-2.3, 1.4)	0.8 (-3.2, 1.8)	-0.8 (-3.2, 1.2)
Jan 10	-0.3 (-7.5, 2.9)	0.4 (-2.3, 2.7)	-0.9 (-3.1, 0.3)	0.4 (-2.7, 1.4)	-0.1 (-2.5, 1.4)
Jan 11	4.6 (-9.8, 5.9)	-1.0 (-4.2, 1.1)	-0.7 (-2.1, 1.5)	-1.0 (-3.3, 3.1)	0.4 (-2.0, 3.4)
Jan 12	0.0 (-8.7, 5.6)	-1.0 (-3.0, 3.5)	0.8 (-1.4, 3.0)	-0.3 (-2.6, 2.3)	-0.2 (-2.8, 2.6)
Jan 13	-0.6 (-10.2, 1.4)	-1.6 (-4.7, 1.6)	-1.8 (-2.9, 0.8)	-0.7 (-3.9, 0.8)	-1.4 (-4.2, 0.1)
Cumulative	-0.2 (-6.3, 1.4)	-0.7 (-2.3, 0.9)	-0.7 (-1.5, 0.7)	-0.6 (-2.5, 0.0)	-0.6 (-2.2, 0.4)

Table 3.14: Daily cause-specific excess inpatient visits due to evacuation. Association between census tract-level evacuation exposure during the 2025 LA fires and excess all-cause and cause-specific inpatient admission rates (per 100,000) in the Kaiser Permanente Southern California catchment area from January 7-13, 2025. Cause-specific visits included cardiovascular, injury, neuropsychiatric, and respiratory. Estimates are from an interrupted time-series design that leveraged machine learning methods to estimate the wildfire-attributable change in visit rates following the LA fires. Each encounter type/exposure category/health endpoint was modeled separately using data from November-January 2022-2025 and time-varying covariates to model pre-fire trends. These 40 separate models were then used to predict expected post-LA fire trends. By comparing the post-fire trends predicted from our models, which served as a counterfactual, to observed post-fire trends, we calculated the excess visit rates attributable to the fires for the 7 days following ignition. 95% empirical confidence intervals were computed using Monte Carlo simulation with 1,000 iterations, using the 2.5th and 97.5th percentiles as the lower and upper bounds.

Percent Excess (95% CI)					
Date	All-cause	Cardiovascular	Injury	Neuropsychiatric	Respiratory
Jan 07	-11.8 (-58.9, 12.7)	-18.7 (-55.9, -0.6)	-11.3 (-36.9, 18.5)	2.7 (-64.4, 17.0)	-24.1 (-163.7, 44.4)
Jan 08	-22.7 (-31.1, 15.4)	-21.9 (-39.1, 7.4)	-5.4 (-25.5, 27.1)	-13.4 (-53.9, 1.5)	0.8 (-53.0, 38.7)
Jan 09	-18.4 (-42.6, 6.8)	-4.5 (-35.5, 6.8)	-17.2 (-19.3, 36.0)	-0.6 (-46.0, 14.2)	-7.9 (-47.0, 15.3)
Jan 10	-1.4 (-43.8, 28.2)	-24.7 (-35.8, 7.6)	-12.4 (-16.7, 42.2)	-13.1 (-34.3, 14.6)	-14.9 (-80.7, 40.3)
Jan 11	-15.3 (-56.6, 21.9)	-21.7 (-32.6, 15.1)	-5.1 (-25.1, 32.0)	0.2 (-25.2, 34.6)	6.2 (-35.1, 43.7)
Jan 12	-9.0 (-62.5, 20.9)	-3.4 (-39.7, 22.2)	-15.3 (-49.3, 17.5)	-11.8 (-107.8, 36.0)	-100.0 (-536.6, 167.8)
Jan 13	-29.2 (-71.6, 1.9)	-16.5 (-70.0, 0.3)	-1.1 (-82.1, 43.8)	-9.9 (-90.7, 58.1)	-19.9 (-33.4, 30.1)
Cumulative	-16.1 (-35.5, 3.5)	-16.3 (-31.7, -1.0)	-11.4 (-14.8, 18.7)	-5.9 (-34.9, 4.4)	-10.5 (-37.2, 12.4)

Table 3.15: Daily cause-specific percent excess inpatient visits due to evacuation in the Eaton zone. Association between residing in the Eaton evacuation zone during the 2025 LA fires and percent change in excess all-cause and cause-specific inpatient admission rates (per 100,000) in the Kaiser Permanente Southern California catchment area from January 7-13, 2025. Cause-specific visits included cardiovascular, injury, neuropsychiatric, and respiratory. Estimates are from an interrupted time-series design that leveraged machine learning methods to estimate the wildfire-attributable change in visit rates following the LA fires. Each encounter type/exposure category/health endpoint was modeled separately using data from November-January 2022-2025 and time-varying covariates to model pre-fire trends. These 40 separate models were then used to predict expected post-LA fire trends. By comparing the post-fire trends predicted from our models, which served as a counterfactual, to observed post-fire trends, we calculated the percent change in excess visit rates attributable to the fires for the 7 days following ignition. 95% empirical confidence intervals were computed using Monte Carlo simulation with 1,000 iterations, using the 2.5th and 97.5th percentiles as the lower and upper bounds.

<i>Excess Visits (95% CI)</i>					
Date	All-cause	Cardiovascular	Injury	Neuropsychiatric	Respiratory
Jan 07	-0.9 (-4.7, 1.0)	-1.1 (-3.4, -0.0)	-0.3 (-0.8, 0.4)	0.1 (-1.3, 0.3)	-0.3 (-2.2, 0.6)
Jan 08	-2.9 (-4.0, 2.0)	-1.7 (-3.0, 0.6)	-0.1 (-0.5, 0.6)	-0.5 (-1.9, 0.1)	0.0 (-1.6, 1.2)
Jan 09	-2.2 (-5.2, 0.8)	-0.4 (-3.0, 0.6)	-0.8 (-0.9, 1.7)	-0.0 (-1.9, 0.6)	-0.3 (-2.0, 0.7)
Jan 10	-0.1 (-4.0, 2.6)	-2.0 (-2.9, 0.6)	-0.6 (-0.8, 1.9)	-0.5 (-1.2, 0.5)	-0.4 (-1.9, 0.9)
Jan 11	-1.3 (-4.7, 1.8)	-1.7 (-2.5, 1.2)	-0.1 (-0.5, 0.7)	0.0 (-1.0, 1.4)	0.3 (-1.7, 2.1)
Jan 12	-0.6 (-4.1, 1.4)	-0.2 (-2.1, 1.1)	-0.2 (-0.6, 0.2)	-0.1 (-1.2, 0.4)	-0.4 (-2.2, 0.7)
Jan 13	-2.5 (-6.1, 0.2)	-1.0 (-4.2, 0.0)	-0.0 (-0.8, 0.4)	-0.1 (-1.0, 0.6)	-1.2 (-2.1, 1.9)
Cumulative	-1.5 (-3.3, 0.3)	-1.1 (-2.2, -0.1)	-0.3 (-0.4, 0.5)	-0.2 (-1.0, 0.1)	-0.3 (-1.2, 0.4)

Table 3.16: Daily cause-specific excess inpatient visits due to evacuation in the Eaton zone. Association between residing in the Eaton evacuation zone during the 2025 LA fires and excess all-cause and cause-specific inpatient admission rates (per 100,000) in the Kaiser Permanente Southern California catchment area from January 7-13, 2025. Cause-specific visits included cardiovascular, injury, neuropsychiatric, and respiratory. Estimates are from an interrupted time-series design that leveraged machine learning methods to estimate the wildfire-attributable change in visit rates following the LA fires. Each encounter type/exposure category/health endpoint was modeled separately using data from November-January 2022-2025 and time-varying covariates to model pre-fire trends. These 40 separate models were then used to predict expected post-LA fire trends. By comparing the post-fire trends predicted from our models, which served as a counterfactual, to observed post-fire trends, we calculated the excess visit rates attributable to the fires for the 7 days following ignition. 95% empirical confidence intervals were computed using Monte Carlo simulation with 1,000 iterations, using the 2.5th and 97.5th percentiles as the lower and upper bounds.

Percent Excess (95% CI)					
Date	All-cause	Cardiovascular	Injury	Neuropsychiatric	Respiratory
Jan 07	12.1 (-20.1, 32.8)	-5.1 (-17.0, 18.6)	48.2 (7.2, 93.4)	-17.5 (-53.4, 29.2)	-2.6 (-116.3, 35.9)
Jan 08	22.9 (-7.8, 55.0)	-19.2 (-15.3, 37.5)	-100.0 (-344.8, 92.6)	-12.1 (-48.5, 44.6)	32.8 (-51.6, 60.3)
Jan 09	19.5 (-15.7, 49.1)	7.5 (-27.1, 25.8)	-32.9 (-52.8, 33.2)	-2.4 (-26.0, 10.3)	-41.0 (-60.1, 31.7)
Jan 10	8.6 (-6.6, 41.8)	8.4 (0.2, 33.9)	-100.0 (-237.2, 34.1)	-15.0 (-36.5, 0.7)	-22.9 (-35.7, 14.3)
Jan 11	1.9 (-16.8, 43.1)	-1.1 (-24.0, 18.2)	-27.3 (-56.7, 26.7)	-8.3 (-18.2, 27.3)	-7.3 (-56.8, 19.7)
Jan 12	17.0 (-5.9, 65.7)	-2.7 (-12.2, 30.2)	46.4 (14.5, 108.9)	-12.0 (-13.1, 29.4)	-100.0 (-359.9, 718.4)
Jan 13	27.2 (-40.8, 71.4)	-5.3 (-17.8, 20.4)	-20.2 (-60.9, 75.0)	-100.0 (-2205.8, 6443.3)	-11.4 (-118.5, 32.0)
Cumulative	14.4 (-4.6, 34.5)	-1.4 (-3.4, 16.3)	-6.0 (-30.8, 39.9)	-10.6 (-20.0, 11.5)	-11.0 (-46.3, 8.0)

Table 3.17: Daily cause-specific percent excess inpatient visits due to evacuation in the Palisades zone. Association between residing in the Palisades evacuation zone during the 2025 LA fires and percent change in excess all-cause and cause-specific inpatient admission rates in the Kaiser Permanente Southern California catchment area from January 7-13, 2025. Cause-specific visits included cardiovascular, injury, neuropsychiatric, and respiratory. Estimates are from an interrupted time-series design that leveraged machine learning methods to estimate the wildfire-attributable change in visit rates following the LA fires. Each encounter type/exposure category/health endpoint was modeled separately using data from November-January 2022-2025 and time-varying covariates to model pre-fire trends. These 40 separate models were then used to predict expected post-LA fire trends. By comparing the post-fire trends predicted from our models, which served as a counterfactual, to observed post-fire trends, we calculated the percent change in excess visit rates attributable to the fires for the 7 days following ignition. 95% empirical confidence intervals were computed using Monte Carlo simulation with 1,000 iterations, using the 2.5th and 97.5th percentiles as the lower and upper bounds.

<i>Excess Visits (95% CI)</i>					
Date	All-cause	Cardiovascular	Injury	Neuropsychiatric	Respiratory
Jan 07	0.5 (-0.9, 1.5)	-0.2 (-0.5, 0.6)	0.7 (0.1, 1.3)	-0.2 (-0.6, 0.4)	-0.0 (-1.2, 0.4)
Jan 08	1.1 (-0.4, 2.7)	-0.5 (-0.4, 0.9)	-0.2 (-0.8, 0.2)	-0.1 (-0.6, 0.5)	0.5 (-0.8, 0.9)
Jan 09	0.7 (-0.5, 1.6)	0.1 (-0.5, 0.5)	-0.5 (-0.8, 0.5)	-0.0 (-0.5, 0.2)	-0.7 (-1.0, 0.5)
Jan 10	0.6 (-0.4, 2.7)	0.5 (0.0, 1.9)	-0.4 (-0.9, 0.1)	-0.4 (-0.9, 0.0)	-0.9 (-1.4, 0.6)
Jan 11	0.1 (-0.7, 1.7)	-0.0 (-0.7, 0.6)	-0.4 (-0.8, 0.4)	-0.3 (-0.6, 0.9)	-0.2 (-1.2, 0.4)
Jan 12	0.6 (-0.2, 2.2)	-0.1 (-0.4, 0.9)	0.6 (0.2, 1.5)	-0.4 (-0.4, 1.0)	0.2 (-1.2, 0.6)
Jan 13	0.6 (-1.0, 1.7)	-0.2 (-0.6, 0.6)	-0.3 (-0.8, 0.9)	0.0 (-0.6, 0.2)	-0.1 (-1.3, 0.4)
Cumulative	0.6 (-0.2, 1.4)	-0.0 (-0.1, 0.5)	-0.1 (-0.3, 0.4)	-0.2 (-0.4, 0.2)	-0.2 (-0.7, 0.1)

Table 3.18: Daily cause-specific excess inpatient visits due to evacuation in the Palisades zone. Association between residing in the Palisades evacuation zone during the 2025 LA fires and excess all-cause and cause-specific inpatient admission rates (per 100,000) in the Kaiser Permanente Southern California catchment area from January 7-13, 2025. Cause-specific visits included cardiovascular, injury, neuropsychiatric, and respiratory. Estimates are from an interrupted time-series design that leveraged machine learning methods to estimate the wildfire-attributable change in visit rates following the LA fires. Each encounter type/exposure category/health endpoint was modeled separately using data from November-January 2022-2025 and time-varying covariates to model pre-fire trends. These 40 separate models were then used to predict expected post-LA fire trends. By comparing the post-fire trends predicted from our models, which served as a counterfactual, to observed post-fire trends, we calculated the excess visit rates attributable to the fires for the 7 days following ignition. 95% empirical confidence intervals were computed using Monte Carlo simulation with 1,000 iterations, using the 2.5th and 97.5th percentiles as the lower and upper bounds.

Percent Excess (95% CI)					
Date	All-cause	Cardiovascular	Injury	Neuropsychiatric	Respiratory
Jan 07	5.9 (-10.7, 19.6)	3.9 (-9.4, 16.3)	3.3 (-12.0, 14.1)	4.5 (-12.9, 9.0)	17.6 (4.7, 34.4)
Jan 08	5.7 (-19.2, 29.2)	-1.1 (-24.6, 23.2)	-2.7 (-22.3, 23.6)	-3.8 (-16.3, 23.5)	29.9 (-27.9, 49.6)
Jan 09	11.6 (-22.3, 36.2)	-5.2 (-22.3, 22.1)	-5.4 (-18.7, 20.0)	-9.1 (-36.5, 15.5)	14.8 (-8.6, 42.4)
Jan 10	1.5 (-17.1, 24.4)	-3.5 (-10.7, 13.2)	-10.4 (-26.2, 13.4)	-2.6 (-24.0, 6.7)	14.0 (-7.4, 33.4)
Jan 11	16.2 (-15.1, 28.8)	-0.1 (-6.8, 24.5)	1.1 (-16.2, 28.4)	6.1 (-6.9, 27.5)	3.2 (-15.3, 38.7)
Jan 12	37.4 (3.4, 51.2)	20.0 (6.2, 39.9)	2.4 (-16.7, 27.7)	8.9 (5.5, 36.5)	10.9 (-7.7, 37.7)
Jan 13	2.7 (-5.4, 16.6)	21.7 (15.2, 35.6)	0.4 (-8.9, 12.7)	15.8 (7.2, 26.9)	0.6 (-11.3, 14.4)
Cumulative	9.8 (-3.4, 18.7)	5.3 (-1.2, 17.2)	-1.5 (-9.6, 10.7)	3.7 (-4.4, 13.8)	11.9 (-1.3, 25.3)

Table 3.19: Daily cause-specific percent excess inpatient visits due to high smoke. Association between census tract-level high smoke exposure during the 2025 LA fires and percent change in excess all-cause and cause-specific inpatient admissions in the Kaiser Permanente Southern California catchment area from January 7-13, 2025. Cause-specific visits included cardiovascular, injury, neuropsychiatric, and respiratory. Estimates are from an interrupted time-series design that leveraged machine learning methods to estimate the wildfire-attributable change in visit rates following the LA fires. Each encounter type/exposure category/health endpoint was modeled separately using data from November-January 2022-2025 and time-varying covariates to model pre-fire trends. These 40 separate models were then used to predict expected post-LA fire trends. By comparing the post-fire trends predicted from our models, which served as a counterfactual, to observed post-fire trends, we calculated the percent change in excess visit rates attributable to the fires for the 7 days following ignition. 95% empirical confidence intervals were computed using Monte Carlo simulation with 1,000 iterations, using the 2.5th and 97.5th percentiles as the lower and upper bounds.

<i>Excess Visits (95% CI)</i>					
Date	All-cause	Cardiovascular	Injury	Neuropsychiatric	Respiratory
Jan 07	1.2 (-2.2, 4.1)	0.5 (-1.3, 2.2)	0.1 (-0.5, 0.5)	0.3 (-0.9, 0.6)	1.5 (0.4, 2.9)
Jan 08	0.9 (-2.9, 4.4)	-0.1 (-2.5, 2.3)	-0.1 (-0.7, 0.7)	-0.2 (-0.8, 1.2)	1.1 (-1.1, 1.9)
Jan 09	1.6 (-3.0, 4.9)	-0.6 (-2.4, 2.3)	-0.2 (-0.6, 0.6)	-0.4 (-1.6, 0.7)	0.8 (-0.5, 2.2)
Jan 10	0.3 (-3.2, 4.6)	-0.5 (-1.4, 1.8)	-0.3 (-0.9, 0.4)	-0.2 (-1.5, 0.4)	1.0 (-0.5, 2.3)
Jan 11	2.2 (-2.1, 4.0)	-0.0 (-0.7, 2.7)	0.0 (-0.5, 0.8)	0.3 (-0.4, 1.6)	0.2 (-0.9, 2.2)
Jan 12	4.6 (0.4, 6.3)	2.0 (0.6, 4.0)	0.1 (-0.5, 0.8)	0.6 (0.4, 2.3)	0.7 (-0.5, 2.4)
Jan 13	0.6 (-1.2, 3.7)	3.0 (2.1, 5.0)	0.0 (-0.4, 0.5)	1.1 (0.5, 1.9)	0.1 (-0.9, 1.1)
Cumulative	1.6 (-0.6, 3.1)	0.6 (-0.1, 2.0)	-0.1 (-0.3, 0.4)	0.2 (-0.3, 0.8)	0.8 (-0.1, 1.6)

Table 3.20: Daily cause-specific excess inpatient visits due to high smoke. Association between census tract-level high smoke exposure during the 2025 LA fires and excess all-cause and cause-specific inpatient admissions (per 100,000) in the Kaiser Permanente Southern California catchment area from January 7-13, 2025. Cause-specific visits included cardiovascular, injury, neuropsychiatric, and respiratory. Estimates are from an interrupted time-series design that leveraged machine learning methods to estimate the wildfire-attributable change in visit rates following the LA fires. Each encounter type/exposure category/health endpoint was modeled separately using data from November-January 2022-2025 and time-varying covariates to model pre-fire trends. These 40 separate models were then used to predict expected post-LA fire trends. By comparing the post-fire trends predicted from our models, which served as a counterfactual, to observed post-fire trends, we calculated the excess visit rates attributable to the fires for the 7 days following ignition. 95% empirical confidence intervals were computed using Monte Carlo simulation with 1,000 iterations, using the 2.5th and 97.5th percentiles as the lower and upper bounds.

<i>Percent Excess (95% CI)</i>					
Date	All-cause	Cardiovascular	Injury	Neuropsychiatric	Respiratory
Jan 07	-9.5 (-33.4, 6.4)	12.4 (-10.3, 23.9)	1.1 (-9.9, 21.0)	8.6 (-21.1, 18.9)	-7.1 (-19.2, 15.4)
Jan 08	-7.2 (-22.9, 13.7)	1.4 (-27.4, 13.7)	-6.9 (-27.1, 7.9)	-9.4 (-26.8, 8.4)	5.8 (-17.0, 28.1)
Jan 09	-13.7 (-42.8, 10.3)	-1.2 (-30.3, 18.7)	-14.4 (-41.1, 19.7)	-8.0 (-41.4, 0.4)	6.9 (-38.1, 28.6)
Jan 10	-0.7 (-23.6, 10.1)	-5.5 (-23.1, 10.5)	-4.2 (-11.0, 16.4)	-10.9 (-44.8, 0.7)	-8.2 (-18.6, 16.9)
Jan 11	-14.7 (-29.3, 5.6)	6.8 (-16.7, 29.0)	-9.2 (-25.0, 11.4)	-10.8 (-26.0, 11.2)	6.3 (-11.1, 35.9)
Jan 12	-10.0 (-51.1, 12.3)	21.5 (-32.2, 45.6)	-0.4 (-27.5, 54.5)	-9.4 (-35.0, 22.3)	-8.9 (-24.6, 43.9)
Jan 13	-2.2 (-17.7, 10.4)	-8.8 (-21.7, 11.5)	-3.9 (-24.4, 9.5)	-8.1 (-24.3, 2.0)	-1.9 (-28.4, 12.9)
Cumulative	-7.9 (-21.5, 2.5)	2.7 (-14.1, 12.4)	-4.9 (-11.6, 6.9)	-6.5 (-22.1, -0.0)	-2.2 (-12.9, 14.0)

Table 3.21: Daily cause-specific percent excess inpatient visits due to moderate smoke.

Association between census tract-level moderate smoke exposure during the 2025 LA fires and percent change in excess all-cause and cause-specific inpatient admission rates in the Kaiser Permanente Southern California catchment area from January 7-13, 2025. Cause-specific visits included cardiovascular, injury, neuropsychiatric, and respiratory. Estimates are from an interrupted time-series design that leveraged machine learning methods to estimate the wildfire-attributable change in visit rates following the LA fires. Each encounter type/exposure category/health endpoint was modeled separately using data from November-January 2022-2025 and time-varying covariates to model pre-fire trends. These 40 separate models were then used to predict expected post-LA fire trends. By comparing the post-fire trends predicted from our models, which served as a counterfactual, to observed post-fire trends, we calculated the percent change in excess visit rates attributable to the fires for the 7 days following ignition. 95% empirical confidence intervals were computed using Monte Carlo simulation with 1,000 iterations, using the 2.5th and 97.5th percentiles as the lower and upper bounds.

<i>Excess Visits (95% CI)</i>					
Date	All-cause	Cardiovascular	Injury	Neuropsychiatric	Respiratory
Jan 07	-2.1 (-7.4, 1.4)	1.8 (-1.5, 3.4)	0.1 (-0.5, 1.0)	0.6 (-1.6, 1.4)	-0.8 (-2.1, 1.7)
Jan 08	-1.5 (-4.9, 3.0)	0.2 (-3.5, 1.8)	-0.3 (-1.2, 0.3)	-0.6 (-1.8, 0.6)	0.4 (-1.1, 1.9)
Jan 09	-2.5 (-7.9, 1.9)	-0.1 (-3.1, 1.9)	-0.3 (-1.0, 0.5)	-0.5 (-2.7, 0.0)	0.4 (-2.1, 1.6)
Jan 10	-0.1 (-5.2, 2.2)	-0.8 (-3.4, 1.6)	-0.2 (-0.6, 0.9)	-0.6 (-2.5, 0.0)	-0.9 (-2.0, 1.8)
Jan 11	-2.9 (-5.8, 1.1)	0.8 (-2.0, 3.5)	-0.3 (-0.8, 0.4)	-0.7 (-1.7, 0.8)	0.4 (-0.7, 2.4)
Jan 12	-1.3 (-6.8, 1.6)	1.6 (-2.4, 3.4)	-0.0 (-0.6, 1.1)	-0.5 (-1.9, 1.2)	-0.6 (-1.6, 2.9)
Jan 13	-0.5 (-4.0, 2.3)	-1.2 (-2.9, 1.5)	-0.1 (-0.8, 0.3)	-0.5 (-1.6, 0.1)	-0.1 (-1.7, 0.8)
Cumulative	-1.6 (-4.3, 0.5)	0.3 (-1.7, 1.5)	-0.2 (-0.4, 0.2)	-0.4 (-1.4, -0.0)	-0.2 (-1.0, 1.1)

Table 3.22: Daily cause-specific excess inpatient visits due to moderate smoke. Association between census tract-level moderate smoke exposure during the 2025 LA fires and excess all-cause and cause-specific inpatient admission rates (per 100,000) in the Kaiser Permanente Southern California catchment area from January 7-13, 2025. Cause-specific visits included cardiovascular, injury, neuropsychiatric, and respiratory. Estimates are from an interrupted time-series design that leveraged machine learning methods to estimate the wildfire-attributable change in visit rates following the LA fires' ignition. Each encounter type/exposure category/health endpoint was modeled separately using data from November-January 2022-2025 and time-varying covariates to model pre-fire trends. These 40 separate models were then used to predict expected post-LA fire trends. By comparing the post-fire trends predicted from our models, which served as a counterfactual, to observed post-fire trends, we calculated the excess visit rates attributable to the fires for the 7 days following ignition. 95% empirical confidence intervals were computed using Monte Carlo simulation with 1,000 iterations, using the 2.5th and 97.5th percentiles as the lower and upper bounds.

CHAPTER 4

AIM 3. ITS2S: A PYTHON PACKAGE FOR TWO-STAGE INTERRUPTED TIME SERIES ANALYSIS USING MACHINE LEARNING

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4.1 Abstract.

Background. When randomized controlled trials are infeasible, researchers may leverage natural experiments for causal inference. Interrupted time-series (ITS) designs compare observed post-event trends to counterfactual predictions from pre-event data. Two-stage ITS designs use flexible models to generate optimized counterfactual predictions in the first stage, then estimate intervention effects by comparing observed to predicted outcomes in the second stage. Fitting high-dimensional versions of these models is challenging, requiring systematic infrastructure to ensure rigor and reproducibility.

Methods. In response, we developed `its2s`, an open-source Python package implementing the two-stage ITS design with machine learning. `its2s` allows users to specify an intervention date and training/testing periods, select among built-in model architectures (e.g., Prophet-XGBoost, NeuralProphet), and generate confidence intervals via moving block bootstrap, preserving temporal autocorrelation in residuals. `its2s` layers defaults, configuration files, and runtime overrides to support workflows ranging from rapid default implementations to highly tailored analyses.

Results. We validated `its2s` using two case studies: a simulation with a 12% policy effect, recovering the true effect as 11.77%, and an analysis of the 2021 Pacific Northwest heat dome, finding 53% excess injury mortality over the following three weeks.

Discussion. `its2s` provides a flexible, reproducible framework for ITS-based quasi-experimental research, lowering barriers to rigorous machine learning-based counterfactual modeling.

4.2 Introduction.

Causal inference is a central goal in health and policy research, where the causal effect is defined as the contrast between outcomes under treatment and outcomes under no treatment for the same units.^{59,66} A randomized controlled trial (RCT) is often considered the gold standard for internal validity, because well-conducted randomization creates two exchangeable groups and researchers control treatment and assessment, allowing them to infer that differences in the outcome can be attributed to the treatment. However, in multiple settings, including environmental exposures or social policies, RCTs are often infeasible or unethical.^{57,78} For example, researchers cannot assign climate disaster exposure to one group and a placebo to another – ruling out an RCT and making causal effects difficult to identify. In these cases, researchers may leverage natural experiments – events such as policy interventions, climate disasters, or disease outbreaks – whose timing is plausibly exogenous to factors driving the trends of a given outcome of interest, thus approximating randomization.⁵⁷ Some quasi-experimental methods exploit this exogeneity to estimate causal effects from observational data, with different designs relying on different strategies to reconstruct the missing counterfactual. Interrupted time series (ITS) designs do so by modeling the outcome's pre-event trend and attributing post-event deviations from that trend to the event of interest. ITS designs are particularly valuable when no credibly comparable control units are available – as is common for climate disasters such as wildfires and heatwaves, and for broad-coverage public health policies.^{74,77,78}

ITS designs are applied to time series data: repeated measurements of an aggregate outcome – such as weekly deaths or daily hospitalizations – collected at regular intervals in a population before and after an event. Beyond random variation, such series typically exhibit systematic temporal structure, including secular trends, seasonality, and temporal autocorrelation. Fundamentally, ITS designs compare observed post-event outcomes to counterfactual post-event outcomes – what would have been expected in the absence of the event.⁷⁷ To estimate this counterfactual, the pre-event portion of the series is used to characterize the temporal structure, which is then projected into the post-event period. The most common implementation uses segmented regression to jointly model pre- and post-event trends as two separate linear segments.^{74,143} This generates estimates

of both immediate level shifts (intercept changes) and longer-term trend shifts (slope changes) following the event.⁷⁷

Besides traditional identification assumptions in causal inference (e.g. correct model specification, no spillover), using ITS designs requires additional assumptions including (1) the event timing is clearly defined, and (2) no other major events sharply affecting the outcome occur concurrently with the event of interest.⁷⁷ Additionally, assumptions about the form of the counterfactual depend on the specific ITS design. In single-group ITS designs (sometimes called single ITS, or SITS), where no contemporaneous control series is available, the design assumes that when projected forward, the pre-event trend accurately represents what would have occurred in the absence of the event. Empirical work has shown that violations of this within-unit counterfactual assumption can be consequential.¹⁴⁴

Beyond these design-level identification assumptions, the most common ITS implementation, segmented regression, has model-specific limitations. First, the researcher must pre-specify the functional form of the underlying trend (typically linear, with optional seasonal or polynomial terms) and the intervention effect (e.g., an abrupt level shift, a gradual slope change, or a lagged response) by hard-coding the corresponding dummy and interaction terms into the model.^{74,78,79} Selecting the functional form after inspecting the post-event data increases the risk of spurious conclusions and has been identified as a primary threat to ITS validity.^{77,144} Second, positively autocorrelated residuals – common in epidemiological time series – deflate standard errors and produce anti-conservative confidence intervals. While corrections such as Prais-Winsten or Restricted Maximum Likelihood with a Satterthwaite degrees-of-freedom adjustment can restore near-nominal coverage in longer series, no method reliably does so in the short series typical of applied ITS studies.^{145,146} Third, segmented regression returns a small set of global parameters (level and slope changes) rather than time-unit-specific excess estimates, limiting its utility for high-dimensional or pooled analyses. To address these limitations, several alternatives have been proposed, including Autoregressive Integrated Moving Average (ARIMA/ARIMAX), Bayesian ITS, and two-stage approaches with machine learning (ML).^{79,143,147}

The two-stage ITS approach with ML is a flexible alternative to single-group ITS models that addresses the limitations specific to segmented regression.^{61,79} The “two-stage” label refers to a deliberate separation of tasks. In the first stage, a flexible ML model (e.g., a hybrid Prophet-XGBoost model) is trained on a subset of pre-event data, with the remaining pre-event data held out for testing and validation. Once a model is selected based on predictive performance, it is used to forecast the post-event period under the counterfactual scenario that pre-event trends would continue absent the event. In the second stage, researchers calculate the effect of the event by comparing the observed post-event series to this counterfactual. Separating these stages strengthens the analysis because (1) since the first-stage model never sees post-event data, the functional form cannot be tuned to the effect it is meant to estimate, and (2) the comparison is made at every time point, yielding a full trajectory of excess estimates rather than one or two global coefficients. Using an ML model further strengthens the credibility of the counterfactual, as flexible learners handle nonlinear trends, seasonality, and autocorrelation without pre-specification of the functional form. As with all single-group designs, the two-stage ML approach inherits the within-unit counterfactual assumption discussed above. However, it avoids the additional assumption required by controlled ITS designs that exposed and unexposed groups have parallel outcome trajectories over time. This is a meaningful advantage when no credible control unit exists. ML flexibility strengthens the credibility of the within-unit extrapolation, but it does not eliminate the assumption. Equally important, because model selection in stage 1 relies only on pre-event data, the impact model is never trained on (and thus never sees) post-event outcomes – structurally removing the data-driven specification bias that can compromise traditional ITS. The two-stage approach also yields time-unit-specific excess estimates rather than a single level or slope coefficient, allowing for richer characterization of dynamic and cumulative effects.⁶¹

Technical and computational barriers may limit uptake of the two-stage ITS approach with ML. Most applied researchers are experts in their respective fields but have limited specialized training in selecting cross-validation strategies, splitting data into training and testing sets, or choosing appropriate ML architectures for time series forecasting. ML approaches are also computationally demanding, and their complexity can make the underlying modeling assumptions difficult to state and test.⁷⁹ Generating valid confidence intervals adds further complexity – methods such as

moving block bootstrap (MBB) preserve temporal dependence by resampling contiguous blocks of residuals rather than individual observations, but require careful selection of block length, which is rarely straightforward.^{61,79} When researchers seek to evaluate multiple events, outcomes, or model specifications, tracking versions and ensuring reproducibility becomes challenging. While analytic code accompanying published applications of the two-stage ML ITS approach is publicly available,⁶¹ to our knowledge, no general-purpose, open-source software package implementing this design exists. Such a package could broaden adoption of the method and more reproducible research.

We developed `its2s`, an open-source Python package that provides a user-friendly implementation of the two-stage ITS approach with ML. The package couples built-in forecasting architectures with fully customizable default configurations. Reproducibility is supported through timestamped, versioned run directories and deterministic seeding across parallel batch runs. Here, we describe the methodological foundation for the two-stage ITS with ML design; detail the `its2s` package implementing this approach, and demonstrate its application through two case studies.

4.3 Methods.

To make the two-stage ITS with ML approach accessible to researchers, we developed `its2s`, an open-source Python package that implements this design with minimal barriers to entry. Users can provide as little as a time series dataset and specification of intervention/event date, leaning on built-in defaults and automation of model fitting, comparison, and effect estimation in `its2s`. Researchers can also leverage the full flexibility of `its2s` to customize every aspect of the workflow from data splitting and cross-validation strategies to hyperparameter tuning ranges and model selection. This flexibility allows researchers to conduct analyses ranging from rapid default implementations to fully customized workflows tailored to their specific research questions, all within a reproducible framework.

In stage 1, `its2s` splits the portion of the time series preceding the event into a training window and a held-out testing window. A ML model is trained on the training window to learn the outcome's

temporal patterns, then evaluated on the testing window to assess out-of-sample predictive power. Since the goal of this model is to forecast the unobservable counterfactual post-event trend, for which we do not know the truth, this evaluation of out-of-sample predictive power is essential. Flexible models can fit their training data well while generalizing poorly,^{148–150} so it is therefore vital to ensure that the counterfactual accurately represents the expected post-event period had the event not occurred. Train/test separation of this kind is the standard approach for evaluating predictive models in ML and time series forecasting; *its2s* makes it a structural, non-optional step of the ITS workflow.^{150–153}

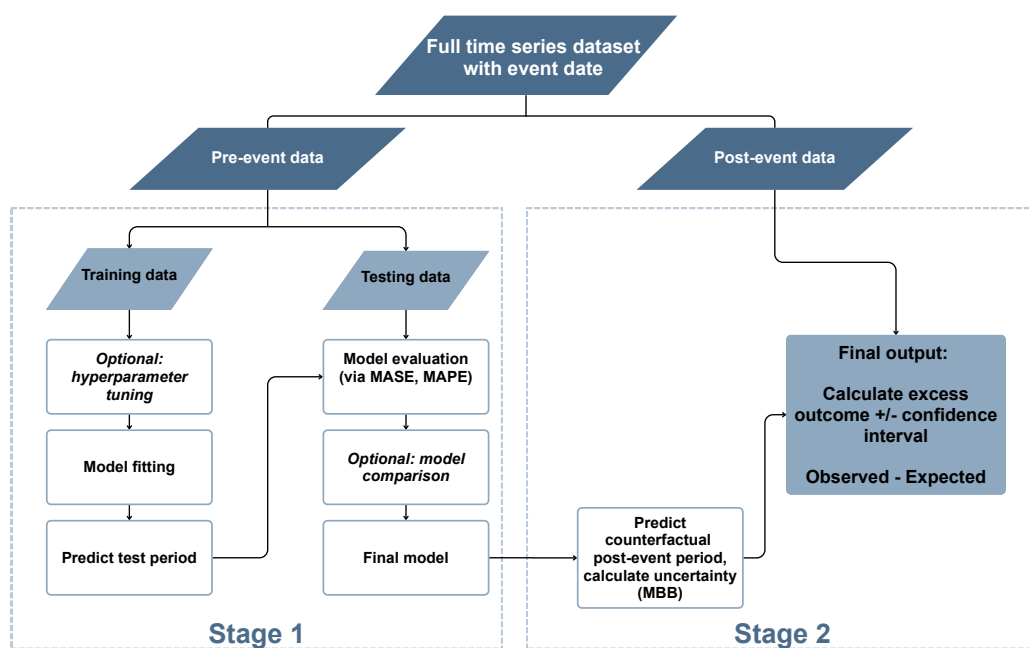


Figure 4.1: Description of *its2s* analytic workflow. Pre-event data is split into training and testing sets to build the Stage 1 model and predict the counterfactual time series. Stage 2 estimates the difference between the observed post-event time series and the counterfactual time series to estimate the causal effect of the event.

The selected model is then used to generate counterfactual predictions for the post-event period (or the holdout, in ML terms) - the expected time series had the event not occurred. In stage 2, *its2s* compares observed post-event outcomes to these counterfactual predictions to estimate the effect attributable to the event. Uncertainty is quantified using moving block bootstraps (MBB),¹⁵⁴

which resamples blocks of residuals rather than individual observations to preserve temporal autocorrelation, following the approach in Dey et al.⁶¹ The statistical theory underlying the two-stage ITS approach is described in more detail in Dey et al.⁶¹

The two stages of the ITS are implemented in `its2s` through a small set of high-level functions organized around a simple core workflow. The primary entry point is `run_single_its()`, which executes the full pipeline for a single outcome series. This function accepts a time series dataframe, an event date, and optional specifications for the target, date, and covariate columns, the forecasting model, a YAML config (via path or runtime overrides), an output directory, and a random seed. The function then splits the pre-event period into training and test windows and fits and evaluates the selected forecasting model in Stage 1. Currently, this package supports the following ML model architectures for this model: (1) Prophet + XGBoost hybrid, (2) NeuralProphet, (3) Prophet then XGBoost, (4) ARIMA. As part of the Stage 1 fit, `its2s` automatically runs residual diagnostic checks via `compute_diagnostics()`, which evaluates the Ljung-Box statistic at pre-defined lags to detect residual autocorrelation¹⁵¹ and applies the Shapiro-Wilk test for normality.¹⁵⁵ These diagnostics directly assess the validity of the moving-block bootstrap used in Stage 2, whose block length governs how much residual autocorrelation the resampling preserves and therefore the coverage of the resulting intervals. The block length may be fixed by the user (the default, specified in observations), or estimated automatically using the Politis and White plug-in rule¹⁵⁶; in addition, `its2s` provides a diagnostic that traces the width of the event-window confidence interval across a range of candidate block lengths, letting the user confirm that the selected length falls in a region where interval width has stabilized. Because no block length restores nominal coverage when the Stage 1 residuals remain strongly autocorrelated, the Ljung-Box diagnostic serves to verify that the fitted model has adequately captured the temporal dependence before the bootstrap is applied. The pipeline returns a `PipelineResult` object containing fitted values, effect estimates, bootstrap confidence intervals, and model diagnostics. All results are accompanied by `plot_counterfactual()`, which produces a standardized figure showing the observed series, in-sample model fit, counterfactual prediction with confidence interval ribbon, and event marker. In the case where the same outcome is studied across multiple geographic units or subgroups, users can use `run_batch()` to produce a list of series, parallelizing execution across cores and writing outputs to automatically versioned

run directories that encode the run date and bootstrap simulation count for all combinations. Configuration at every step is managed through a YAML file loaded via `load_config()`, which specifies the split method, bootstrap parameters, and model hyperparameters; any parameter can be overridden at runtime via the `config_overrides` argument, and all overrides are documented in the model outputs, providing a reproducible specification that can be version-controlled alongside the data and code.

For researchers who want to interrogate model selection before committing to a final run, `its2s` also provides a set of pre-analysis tools: `compare_models()` runs all available model architectures on the same series and returns a ranked comparison table, `tune_model()` searches the hyperparameter space for a chosen model via Latin hypercube sampling, and `time_series_cv()` evaluates a single model's out-of-sample performance across expanding folds independently of a full pipeline run.

We illustrate the package's application in two case studies. First, we evaluate `its2s` using a simulated daily healthcare utilization series with a known ground-truth intervention effect – a synthetic +12% level shift imposed on March 1, 2025 – to assess how well the estimated counterfactuals recover the true effect. Second, we use counts of weekly injury deaths in Washington State from the US Centers for Disease Control and Prevention (CDC) to study the impact of the June 2021 Pacific Northwest heat dome, treating this extreme weather event as a natural experiment.

`its2s` is maintained on GitHub. All extended documentation can be accessed on the `its2s` website [here](#).

4.4 Case studies.

Here we illustrate the utility of `its2s` in two case studies. Case study 1 leverages simulated data to recover the effect of a policy intervention on daily healthcare encounters. Case study 2 uses CDC Wonder data to quantify the impact of the 2021 Pacific Northwest heat dome on injury mortality in Washington state. The case studies are intentionally simple implementations of `its2s`, using predominantly default settings to illustrate the packages' out-of-the-box utility.

4.4.1 Case study 1: simulated policy intervention.

Background. Case study 1 is a simulation representing a daily time series of healthcare utilization counts for a single geographic unit from January 2022 through December 2026, with a synthetic policy intervention on March 1, 2025. To generate these data, we imposed a baseline of ~ 800 visits per day with a moderate upward trend, annual seasonality (peak in early January), day-of-week effects (weekdays higher than weekends), and lower utilization on US federal holidays ($\sim 18\%$ reduction). We sampled daily counts from a Poisson distribution. Beginning on the intervention date, we imposed a constant multiplicative $+12\%$ level shift on the rate. We then use `its2s` to estimate the intervention effect, providing a ground truth against which to evaluate `its2s`.

Methods. We use `its2s` with default settings and a Prophet + XGBoost model (default model) to fit the pre-intervention period. We reserved the last 20% of pre-intervention days for a testing set, using all remaining pre-intervention days as training data (default configuration). Our holdout was comprised of all post-event data (2025-03-01 through 2026-12-31). Uncertainty was generated using a MBB (default block length of 14 observations, equal to 14 days on this daily series). We estimated the change in utilization as the difference between the observed utilization count (from simulated time series) and the expected rate (counterfactual predicted from the model we fit on pre-intervention data).

Results. During the 671-day post-intervention holdout period (2025-03-01 through 2026-12-31), we estimated an 11.77% excess visit rate (95% eCI: 10.23%, 12.96%), approximately the true 12% level shift. The Prophet - XGBoost model fit the pre-event test time series reasonably well ($MAPE = 3.9\%$) (Figure 4.2), facilitating the recovery of an effect size resembling the true effect.

4.4.2 Case study 2: 2021 Pacific Northwest (PNW) heat dome.

Background. In the context of a warming climate, extreme heat is a growing public health concern linked to elevated mortality not only from cardiovascular and natural causes, but increasingly due

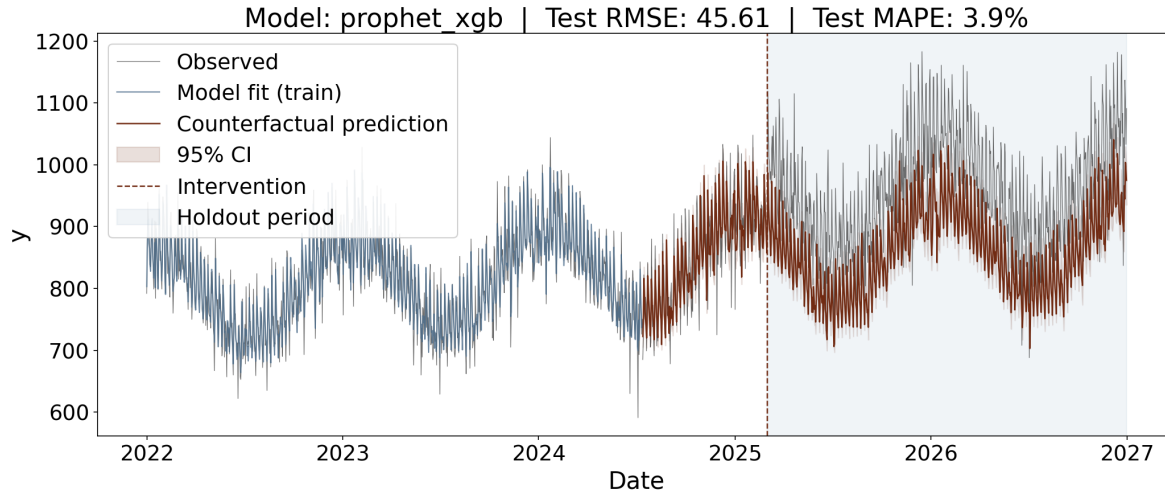


Figure 4.2: Case study 1: simulation. Case study 1: simulated daily data (grey), pre-intervention model fit (blue), and counterfactual prediction with uncertainty for the post-intervention holdout (red; Prophet + XGBoost). Dashed green line represents timing of event.

to injuries (e.g., suicide, drowning, transportation accidents, or occupational accidents in construction or agriculture).^{157–160} Though historically the Pacific Northwest region of the US has a mild summer, in late June and early July, 2021, the region recorded its highest-ever temperatures due to a ‘heat dome’ where persistent high-pressure atmospheric system trapped and compressed.¹⁶¹ The unprecedented heat among a population with limited previous exposure to such temperatures and relatively little preparedness may have caused substantial excess mortality.^{158,161} In this case study, we treat the heat dome as a random shock and use *its2s* to apply an ITS analysis to study subsequent changes in weekly injury deaths in Washington State.

Methods. We analyzed weekly counts of injury deaths in Washington State from January 2014 through July 2021 from CDC Wonder¹⁶² to estimate changes in injury mortality in the 3 weeks following the 2021 Pacific Northwest (PNW) heat dome (intervention date 2021-06-25; holdout weeks beginning 2021-06-26, 2021-07-03, and 2021-07-10). This analysis mirrors that of Casey et al. 2023 (¹⁵⁸), who used ARIMA modeling. Our case study built a model using most of the default *its2s* settings. Given the strong seasonal temperature trends, we did not use default settings for the train/test split. Instead, we adjusted it to lengthen the training period in order to ensure sufficient training data for the model to capture the seasonality sufficiently. We thus fit a new model on

pre-event data (379 pre-event weeks and reserving 11 weeks (78 calendar days, 2.8% of pre-intervention observations) for out-of-sample testing immediately before 25 June 2021, a deviation from the default). We achieved a reasonable fit on these parameters, though future iterations could adjust the default settings further, too. The counterfactual time series was generated for the 3 weeks following the event, and uncertainty was quantified using MBB. The change in injury deaths was defined as observed minus expected (counterfactual) counts during the post-event holdout period.

Results. During the 3-week holdout, we estimated 193 excess injury deaths (95% eCI: 179, 217) relative to the counterfactual, corresponding to a 53% excess (eCI: 49%, 60%). Excess injury-related mortality was highest in the middle week (week beginning 2021-07-03: 104 excess deaths [99, 118]), when observed counts reached 229 versus ~ 125 expected. The Prophet-XGBoost model fit the pre-event test time series reasonably well ($MAPE = 5.5\%$) (Figure 4.3).

This case study capitalizes on the random timing of the 2021 PNW heat dome to estimate changes in injury mortality attributable to the event. These results are comparable to Casey et al., who reported 159 excess injury deaths (95% CI: 122, 195) over a comparable 3-week window¹⁵⁸. Our estimates in this ITS analysis are of similar magnitude and show that `its2s` can be applied in a few lines of code using default workflow settings. This analysis had many limitations – including lack of time-varying covariate adjustment and weekly aggregation, which may mask important daily changes in mortality – but demonstrated a user-friendly implementation of the package for a well-defined shock.

4.4.3 What we learn from these case studies.

Together, these case studies show `its2s` applied with minimal API calls and largely default settings across two complementary settings – a simulated policy intervention in which the package closely recovered a known +12% level shift, and a real extreme-heat mortality application yielding plausible excess estimates. Both examples are illustrative, and are meant to highlight a single workflow for internal validation when ground truth is available. Real-world implementations may range from

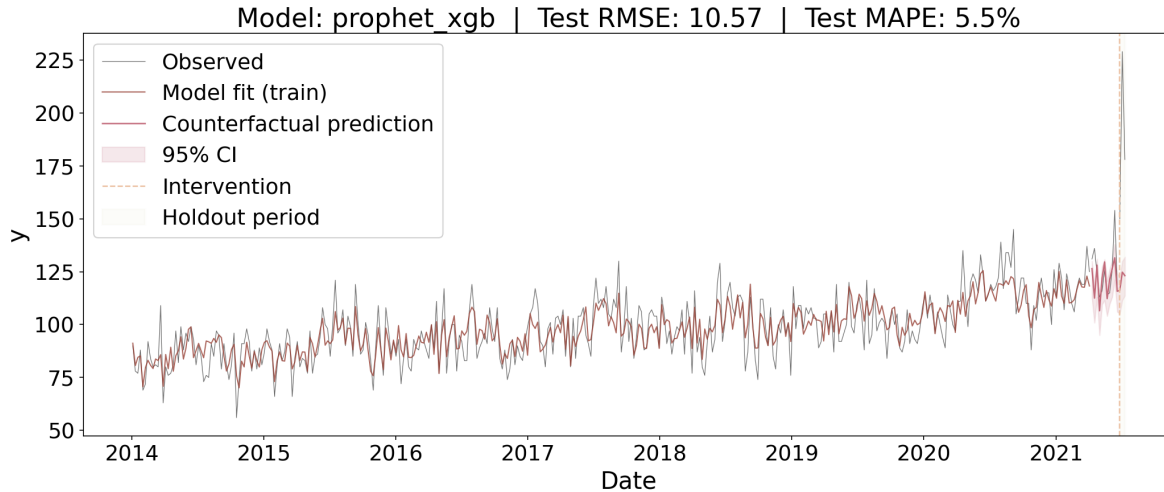


Figure 4.3: Case study 2: Pacific Northwest heat dome. Case study 2: observed weekly injury deaths in Washington State (grey), model fit on pre-intervention data (blue), and counterfactual prediction with uncertainty for the 3-week post-heat-dome holdout (red; Prophet + XGBoost). Dashed green line represents timing of event.

simple applications as demonstrated here to more complex ones that involve (1) covariate adjustment, (2) custom hyperparameter choices, (3) multi-model comparison frameworks, or (4) dynamic block length selection for estimating uncertainty using MBB.

4.5 Discussion.

The objective of employing a two-stage ITS with ML approach is to estimate the effects of an event or intervention by capitalizing on the timing of natural experiments. ITS can be applied to a wide range of natural experiments, including climate shocks (e.g., extreme heat events, wildfires, hurricanes), social or urban policies (e.g., alcohol control policies, protected bike lane) or healthcare policies (e.g., Medicaid expansion). The `its2s` software package allows users to readily implement this study design. The package provides a structured and documented tool for each decision point in the analytical process: `time_series_cv()` for evaluating out-of-sample performance, `compare_models()` for comparing model architectures, `tune_model()` for searching the hyperparameter space along options to use data-driven block-length selection for the bootstrap. `its2s` serves both straightforward use cases, allowing researchers to obtain results quickly with built-in

defaults, and advanced use cases with customized pipelines.

Improving model performance – through model selection, covariate specification, or hyperparameter tuning – is the primary lever for strengthening the causal estimates produced by the two-stage ITS approach.^{61,77} However, achieving good test performance requires researchers to navigate a large and interdependent space of methodological decisions.^{79,146,163} First, researchers must determine the amount of pre-intervention data to reserve for testing, where too short a test window yields unstable performance metrics, while too long a window leaves too little training data – and the right balance depends on the total length of the pre-intervention series.^{150,152} Once the data are split, researchers need to choose from different model architectures, each with different assumptions about trend, seasonality, and residual structure.^{77,79,164,165} Evaluating candidates systematically requires time-series cross-validation, which introduces further structural choices (e.g., the number of folds, the validation window length, and the skip gap between folds needed to prevent information leakage into the held-out test period).^{152,153} Once a model is selected, searching the hyperparameter space adds another layer as each architecture exposes a distinct configuration space, and evaluating it systematically requires running many cross-validated fits whose cost grows with series length and model complexity.^{79,165} Further, when estimating uncertainty, for the MBB, the appropriate length should theoretically reflect the autocorrelation structure of model residuals – a structure that varies across series and model specifications.^{79,154,156,166} This means that a single fixed value for the block length is rarely justified, adding a further analytical decision after the model is fit.

These challenges scale sharply in typical epidemiological applications, where the same analytic steps often need to be repeated across multiple geographic units, age groups or other strata, and outcome types within a single study, and where sensitivity analyses may necessitate varying the training window, cross-validation specifications, or model specifications across an additional set of runs. By automating configuration management, batch processing, and version tracking, *its2s* eliminates much of the time-consuming and error-prone infrastructure burden. This allows researchers to focus on scientific decision making – hyperparameter tuning, model selection, interpretation – rather than maintaining *ad hoc* hard-coded scripts and tracking systems.⁷⁹

While `its2s` is well-suited for time series analyses with sufficient observations, a clearly defined event or intervention, and data over a relatively long time period (e.g., enough training data to span a full cycle of seasonality), the package has several limitations.

First, this package inherits all the limitations of an ITS design. The validity of the ITS design relies on effective counterfactual estimation, which requires an unverifiable assumption – that pre-event trends would extend into the post-event period absent the event of interest. While strong out-of-sample predictive power is a reasonable indicator of the model’s ability to generalize, it cannot ensure an accurate counterfactual. The design also assumes that no other shock coincides with the event of interest, which only the researcher, not the package, can check. Additionally, the ITS design is not a good fit for studies involving events or interventions with uncertain timing or prolonged duration. From a package perspective, the flexibility of `its2s` risks overfitting – requiring researchers to carefully test and validate models. Additionally, while `its2s` provides functionality to run large batches of different models, it does not handle model-specific customization automatically – this remains a decision for the research team. Finally, while `its2s` provides a computationally efficient framework, computational demands still scale substantially as datasets grow, batches increase, or hyperparameter grids expand.

When exposures cannot be randomized, natural experiments allow researchers to recover causal effects from abrupt exogenous shocks. If the timing of an event is assumed at-random with respect to other outcome determinants, using a population’s own pre-event trajectory can serve as the counterfactual for what would have occurred in the absence of the event – and the difference between the observed and expected outcome trajectories can be interpreted causally. Among the strongest methods for studying these natural experiments is the ITS design. The two-stage ITS with ML approach enhances this method by estimating a counterfactual that flexibly captures complex temporal and seasonal trends. This flexibility introduces methodological and computational barriers to entry that have limited its adoption. We introduce `its2s` as a solution, providing a standardized, reproducible, computationally efficient implementation of the method accessible to all skill levels. `its2s` expands the toolkit for leveraging natural experiments to conduct rigorous, reproducible causal inference – allowing researchers to rapidly and reproducibly quantify the impacts of exogenous shocks and policy interventions.

CHAPTER 5

CONCLUSION

5.1 Overview.

In the context of escalating, co-occurring, and compounding wildfires and power outages, understanding the effects of these climate disasters on population health is essential to protecting both humans and the environment through policy and regulation. However, studying these climate disasters – and particularly how they affect the most vulnerable communities – is methodologically challenging. Doing so credibly requires comparing an exposed population to a counterfactual population to determine the effect of the disaster on health outcomes. This dissertation applied two self-controlled quasi-experimental designs that build such counterfactuals from observational data. Specifically, I leveraged the time-stratified case-crossover design and two-stage ITS with machine learning approach. I demonstrate these quasi-experimental designs through two applied aims, each contributing substantively to our understanding of wildfires and power outages – specifically planned PSPS events – and their effects on health. A third aim then generalizes the two-stage method into an open-source software package for the broader research community.

5.2 Summary of key findings.

5.2.1 Aim 1: PSPS, wildfires, acute healthcare utilization.

The first aim of this dissertation used a time-stratified case-crossover design to estimate the independent and joint health effects of wildfire smoke and public safety power shutoffs (PSPS), a previously unexamined climate adaptation strategy meant to prevent wildfires. Leveraging circuit-level power outage data and modeled wildfire PM_{2.5} estimates,^{85,167} we found that the odds of same-day respiratory and COPD-specific encounters were elevated following a severe PSPS event. Importantly, we found evidence of multiplicative interaction between severe PSPS events and wildfire PM_{2.5} exposure for respiratory- and COPD-related encounters, with the strongest and most consistent effects for those with COPD or over 65 years.

The case-crossover study design is self-controlled and well-suited to studying abrupt, well-defined,

and co-occurring exposures like PSPS events and wildfire smoke, where individual-level confounders are unlikely to change over the short exposure window. As wildfire risk drives continued and expanding use of PSPS events as a mitigation strategy, understanding their unintended health consequences is critical to ensuring that efforts to reduce wildfire risk do not introduce new health harms.

5.2.2 Aim 2: 2025 LA fires.

The second aim of this dissertation used a two-stage ITS with machine learning approach to estimate the effects of the unprecedented 2025 LA fires, where both smoke and evacuation impacted nearby populations, on emergency department and inpatient healthcare utilization. Given high winds and limited ground-based monitoring, we used National Oceanic and Atmospheric Administration (NOAA) HYSPLIT trajectories to accurately ascertain $PM_{2.5}$ exposure following these fires. We also leveraged evacuation polygons from county governments, which, together with our smoke exposure assessment, allowed us to examine how these two components of the wildfire disaster may have separately impacted healthcare utilization. In the week following ignition, among those exposed to heavy smoke, cardiovascular and neuropsychiatric visits increased, while respiratory visits declined. Among those in evacuated areas, we found an overall reduction in care-seeking, though this varied across areas and may reflect differences in socioeconomic status and other household-level factors.

The two-stage ITS design allowed us to build a counterfactual for an abrupt, single shock that otherwise would not have had a reasonable comparison population, making it possible to quantify the effects of these fires on healthcare utilization – work that will become increasingly vital as fires of this nature become more frequent and widespread.

5.2.3 Aim 3: *its2s*.

The third aim of this dissertation generalized the method used in aim 2 – the two-stage ITS with machine learning design – by developing an open-source Python package, *its2s*, for user-friendly implementation of this approach. *its2s* lowers the barrier to entry and makes it substantially easier for researchers to apply the two-stage ITS method to their own data. This work is featured on its website and was presented at the 2026 International Society for Environmental Epidemiology North American Chapter meeting in Baltimore, Maryland. Understanding how climate disasters affect health, and developing rigorous methods to study these effects, is critical – but accessible implementation of these methods depends on the availability of usable tools. Contributing to the larger environmental epidemiology toolkit is therefore essential to advancing the study of climate disasters and health.

5.3 *Future directions.*

Together, this dissertation’s three aims advance the foundation of quasi-experimental methods for environmental epidemiology, demonstrating the ways in which causal inference approaches may be adapted to characterize how climate disasters affect health. Yet, substantial methodological, substantive, and computational gaps remain – as climate disasters, particularly wildfires, grow to affect more places and people, findings must be validated across different populations, and tools to study them must be refined and scaled.

5.3.1 *The shifting landscape of climate disasters.*

A changing hazard landscape.

Climate disasters are no longer rare nor geographically confined events. Further, new and understudied mitigation strategies designed to address them are also expanding. Wildfires and PSPS events, the focus of this dissertation, exemplify this pattern. As human populations and wildfires continue

to converge in the expanding WUI, a growing number of people are exposed to wildfire burn zones, wildfire PM_{2.5}, and associated disruptions such as evacuation. Utilities have increasingly used PSPS events as a strategy to reduce the risk of wildfires. These events can cut power to hundreds of individuals, with potential health implications. Further, wildfires can still ignite even after a PSPS event has been initiated, exposing populations to simultaneous power outages and wildfire smoke. This pattern, where mitigation of climate hazards can harm health and co-occur with the hazard they are meant to prevent is likely to repeat across other hazard-mitigation pairs, such as flooding and closing of flood gates. Such shifts necessitate not only studying the joint effects of these hazards and mitigation strategies, but also studying larger and more diverse geographic areas exposed to them. As the breadth of inquiry in this field expands, it is also essential to continue developing methods and methodological tools to do so.

The energy transition.

Massive shifts in energy infrastructure have the potential to ameliorate health impacts of climate disasters, shifting the landscape of climate epidemiology. To date, the cost of solar and battery storage has declined rapidly and much faster than predicted – and is projected to continue to decline.¹⁶⁸ Further, deployment of distributed energy resources, including solar power and battery storage, will also enhance grid resilience, particularly during a climate hazard such as a wildfire.^{169,170} As these technologies become more affordable, these shifts will theoretically reduce the number of customers affected by power outages – thereby reducing dual exposure to wildfires and power outages. Potentially lowering exposure or introducing different unintended consequences, this transition will be critical to the study of climate disasters and health – particularly those that co-occur with power outages.

A shifting exposed population.

Beyond the nature of climate exposures themselves, the nature of who is exposed to these disasters – and where – is likely to shift. Population movement into the WUI continues to grow, placing a growing number of people in the path of wildfires.⁶ Simultaneously, climate-driven out-migration

from high risk areas has started for many climate disasters – though it is currently less common for wildfires and occurs with just the most severe events, this pattern is likely to grow to mimic other disasters.^{171–173} Further, home insurance incentives have both push and pull effects on people living in high wildfire risk areas, and these markets will continue to evolve as the landscape shifts.¹⁷⁴ In the highest-risk areas, regular insurance companies are expected to cover fewer homes over time — by 2055, their share of the market could drop by 5 percentage points as prices rise and coverage worsens. That means more homeowners will likely end up relying on the state’s backup insurance plan or pricier, less-regulated insurers just to stay covered.¹⁷⁴ These counteracting trends will reshape the nature of exposure to climate disasters in the coming years.

5.3.2 Improving exposure and outcome assessment.

Improving exposure assessment is essential to successful environmental epidemiological inquiry. Often, exposure assessment is based on ambient conditions at the residential address. However, this assumes people are home during the exposure window – an assumption that may not hold for the full duration of most environmental exposures. An individual may be exposed to high wildfire PM_{2.5} at work and during transit, for example, followed by low exposure after work, yet residential address-based assignment would assign this individual only low wildfire PM_{2.5} exposure. Even when individuals remain at home for the duration of an exposure, residential address alone does not always capture true exposure. Ambient air quality data cannot account for individual behavior indoors – whether windows are open or closed, whether a HEPA filter is used, or how much time is spent inside versus outside – while indoor air quality monitors, conversely, fail to capture conditions in the ambient outdoor environment. Often, the true split between indoor and outdoor exposure is simply unknowable. Even knowing this split does not resolve the misclassification, because indoor air quality itself responds to outdoor smoke in non-uniform and often unmeasured ways. The median indoor PM_{2.5} rises on wildfire smoke days even as people close windows and run air filters, such that outdoor exposure rarely translates directly into personal exposure.^{175,176} Without knowing both the individual splits of time spent indoor-outdoor, as well as the size of the gap between indoor and outdoor PM_{2.5}, accurately determining exposure remains challenging. Beyond these

measurement challenges, wildfire PM_{2.5} is not a uniform exposure – its chemical composition, which varies substantially by fuel type, combustion conditions, and meteorological factors, may make it more harmful than ambient PM_{2.5} from other sources at equivalent concentrations.²¹ Residential exposure assignment also fails to capture longer-term consequences of wildfire smoke, including the cumulative effects of repeated PM_{2.5} infiltration into homes or the potential downstream effects on soil or water quality.

Researchers consistently seek to improve methods for exposure assessment in environmental epidemiology, including both how exposures are measured and how they are assigned to individuals. With respect to measuring the exposure itself, novel data sources increasingly allow for more granular spatiotemporal quantification of environmental hazards. In aim 2 of this dissertation, for example, we leveraged NOAA HYSPLIT trajectories in place of stationary EPA monitor data to more precisely ascertain where wildfire PM_{2.5} was present given strong, directional Santa Ana winds – an approach that allowed for continuous measurement over time and precise spatial placement of smoke. As these data become more accessible, future research will be better equipped to capture the complexity of environmental exposures at more granular spatiotemporal resolutions. With respect to assigning this exposure to individuals, future research may leverage new technologies such as wearable devices, smartphone mobility data, or low-cost personal PM_{2.5} sensors, offering the potential for more accurate individual-level exposure ascertainment. Researchers may also consider leveraging internet-connected devices to determine individual-level exposure, though it is important to consider both individual-level power outage exposure as well as the larger community-level disruption of a power outage in an area where many people and businesses lost power, even if a given individual did not lose power.

The other piece to better understanding the exposure-outcome relationship with greater accuracy is improving the outcome data used. Future research should consider data sources that allow studies to measure adverse health outcomes directly, alongside healthcare utilization, as these capture distinct but complementary phenomena – healthcare utilization reflects care-seeking behavior in addition to population health, while direct health outcomes reflect the underlying health in the population. Healthcare utilization data can miss people who lack health insurance, live far from care, or choose not to seek care for other reasons. Both healthcare utilization and health status

are important endpoints, but capture different outcomes. Additionally, leveraging data sources that capture health in the population more broadly would allow researchers to generate more generalizable results. To do this, researchers could leverage electronic health record (EHR) data to set up rapid cohort studies or collect biospecimens among large groups in the aftermath of a disaster. EHR-based outcomes could be validated through high-quality subsets to quantify sensitivity and specificity, adding further credence to results.

5.3.3 Advancing methods.

Causal inference relies on credible counterfactuals. Building credible counterfactuals from observational data remains the central methodological challenge in environmental epidemiology – and the fundamental problem is that the true counterfactual, what would have happened in the absence of a climate disaster, is by definition unobservable. Quasi-experimental designs such as time-stratified case-crossover studies and two-stage ITS approaches offer powerful tools for approximating these comparisons, but no method can confirm whether its counterfactual is correct. In the two-stage ITS with machine learning approach, for example, the ML-generated counterfactual rests on the assumption that pre-disaster trends would have continued had the disaster not occurred – an assumption that cannot be directly tested. Future research should develop more rigorous approaches to characterize uncertainty around this assumption, including alternative hold-out strategies, comparisons across modeling specifications, and simulation studies under known data-generating processes.

At the same time, existing quasi-experimental designs often estimate the effects of one hazard at a time, yet climate disasters rarely occur in isolation. Extending self-controlled designs to jointly estimate the effects of co-occurring exposures and to capture the compounding effects of repeated or sequential hazard exposure on the same population over time will be critical for the future of this field as climate change accelerates. This type of research will require further methods development to compute increasingly complex counterfactuals.

5.3.4 Lowering barriers to entry.

A major barrier to advancing these methods remains accessibility. Working with large, heterogeneous data sources and adopting complex quasi-experimental methods requires both computational infrastructure and subject-matter expertise. Closing this gap requires prioritizing both open-source software and openly available training resources – so that scientists can focus on the scientific questions rather than the computational ones. In practice, this may include conference workshops and open tutorials built around real datasets, well-documented open-source packages, or AI coding assistants that lower the barrier to implementing unfamiliar methods correctly. It means both providing the tools and training the researchers to use those tools.

5.3.5 Generalizability and transportability.

The findings presented in this dissertation may not generalize beyond the specific utility regions, health systems, and populations studied in California. While California is a suitable place to study wildfires and health given the frequency and diversity in exposure, replication across other states, fire regimes, power grids, and health data systems is therefore critical – both to validate these findings and to understand the conditions under which they may or may not hold.

5.4 Policy and intervention implications.

As climate disasters intensify and their health consequences become better understood, the quality of the evidence used to inform policy responses is essential. Generating causal, rather than merely associational, evidence is essential to informing the policies and regulations designed to protect population health in the context of climate disasters. Associational evidence can identify patterns, but causal evidence is required to confidently attribute health effects to specific exposures and to propose appropriately targeted regulatory action. The findings of this dissertation contribute to this evidentiary base for two specific climate hazards – wildfire PM_{2.5} and PSPS events.

With respect to wildfire PM_{2.5} specifically, the findings here support continued refinement of guidance and regulation around air quality, particularly for vulnerable populations. Policymakers should consider additional protections for older adults, individuals with chronic conditions such as COPD, and people reliant on eDME. Medicare could, for example, consider covering devices such as HEPA filters or backup batteries, particularly for these populations. Such action would likely result in cost-savings, in addition to improved health in these vulnerable groups.

Beyond mitigating exposure, health systems and payers should also consider how to prepare for the wildfire PM_{2.5} exposure during these disasters in advance. This may include pre-emptively reaching out to patients with respiratory or cardiac conditions ahead of forecasted smoke events, or establishing surge-capacity protocols for emergency departments and virtual care during smoke waves. Emergency Medicare and Medicaid provisions – such as early prescription refills or coverage for portable backup power for medical equipment during declared PSPS or wildfire disasters – may further reduce these harms.

Utilities, forest management agencies, and public health regulators may also consider the tradeoffs between mitigation strategies, such as prescribed burns or PSPS events, and their unintended consequences on population health. For example, findings indicate that moderate prescribed burning reduced total population-weighted wildfire PM_{2.5} exposure by more than half, relative to no-burn scenarios, but that these health benefits plateaued – prescribed burn-specific PM_{2.5} begins to rival wildfire PM_{2.5} at higher levels.¹⁷⁷ PSPS events are typically triggered based on a utility's cost-benefit calculation of wildfire risk against service disruption, one that does not explicitly weigh the health consequences of the outage itself. The findings in this dissertation make the case for incorporating exactly this kind of evidence into that decision-making framework. For PSPS events specifically, particular attention should be paid to populations who are most vulnerable to power outages, including those who rely on eDME and older adults aging in place.

However, power outages carry their own risks to health and wellbeing, and this tradeoff must be weighed as well. Utility-caused wildfires are common and devastating, but they largely stem from grid infrastructure that has been chronically undermaintained – fragile, above-ground lines that are especially vulnerable to high winds during fire season. Burying power lines and other proactive grid

upgrades could reduce reliance on PSPS as a mitigation tool altogether, avoiding both the ignition risk and the health harms of the outages used to manage it. However, who bears the cost of these upgrades, and how that responsibility should be distributed, remains an open question.

As the energy transition reshapes the grid, as we consider other mitigation strategies, ensuring that distributed energy resources are accessible to these populations will be essential to protecting them from wildfires and their mitigation efforts alike. Across both hazards, protections and preparedness resources should be prioritized for the communities that are most exposed and least equipped to respond.

5.5 Conclusion.

The escalating frequency and complexity of climate disasters requires rigorous causal inference methods to generate the evidence needed to understand impacts on population health so that protective measures can be put into place. This dissertation contributes to the development and application of quasi-experimental designs well-suited to studying the effects of these events on health. The first two aims apply two such self-controlled designs, a time-stratified case-crossover study and a two-stage ITS with machine learning approach, to characterize the effects of wildfires and associated planned power outages on health. The third aim extends the ITS framework and lowers the barrier to its implementation through the development of open-source software to implement the design. With the intensification of climate disasters, the populations affected will be more diverse and the exposures more complex – and the credibility of the evidence used to protect them will depend on the rigor of the causal inference methods used to generate it.

BIBLIOGRAPHY

- [1] NASA. Evidence, 2024. URL <https://science.nasa.gov/climate-change/evidence/>.
- [2] Anthony L Westerling, Hugo G Hidalgo, Daniel R Cayan, and Thomas W Swetnam. Warming and earlier spring increase western US forest wildfire activity. *science*, 313(5789):940–943, 2006.
- [3] John T Abatzoglou and A Park Williams. Impact of anthropogenic climate change on wildfire across western US forests. *Proceedings of the National Academy of sciences*, 113(42):11770–11775, 2016.
- [4] Philip E Dennison, Simon C Brewer, James D Arnold, and Max A Moritz. Large wildfire trends in the western United States, 1984–2011. *Geophysical Research Letters*, 41(8):2928–2933, 2014.
- [5] Virginia Iglesias, Jennifer K Balch, and William R Travis. US fires became larger, more frequent, and more widespread in the 2000s. *Science advances*, 8(11):eabc0020, 2022.
- [6] Volker C Radeloff, David P Helmers, H Anu Kramer, Miranda H Mockrin, Patricia M Alexandre, Avi Bar-Massada, Van Butsic, Todd J Hawbaker, Sebastián Martinuzzi, Alexandra D Syphard, and others. Rapid growth of the US wildland-urban interface raises wildfire risk. *Proceedings of the National Academy of Sciences*, 115(13):3314–3319, 2018.
- [7] Matthew D Hurteau, Anthony L Westerling, Christine Wiedinmyer, and Benjamin P Bryant. Projected effects of climate and development on California wildfire emissions through 2100. *Environmental science & technology*, 48(4):2298–2304, 2014.

- [8] Minghao Qiu, Jessica Li, Carlos F. Gould, Renzhi Jing, Makoto Kelp, Marissa L. Childs, Jeff Wen, Yuanyu Xie, Meiyun Lin, Mathew V. Kiang, Sam Heft-Neal, Noah S. Diffenbaugh, and Marshall Burke. Wildfire smoke exposure and mortality burden in the USA under climate change. *Nature*, 647(8091):935–943, November 2025. ISSN 1476-4687. doi: 10.1038/s41586-025-09611-w. URL <https://www.nature.com/articles/s41586-025-09611-w>.
- [9] Shu Li and Tirtha Banerjee. Spatial and temporal pattern of wildfires in California from 2000 to 2019. *Scientific reports*, 11(1):8779, 2021.
- [10] Marshall Burke, Anne Driscoll, Sam Heft-Neal, Jiani Xue, Jennifer Burney, and Michael Wara. The changing risk and burden of wildfire in the United States. *Proceedings of the National Academy of Sciences*, 118(2):e2011048118, 2021.
- [11] Miriam Greenberg, Hillary Angelo, Elena Losada, and Christopher C. Wilmers. Relational geographies of urban unsustainability: The entanglement of California’s housing crisis with WUI growth and climate change. *Proceedings of the National Academy of Sciences*, 121(32): e2310080121, August 2024. ISSN 0027-8424, 1091-6490. doi: 10.1073/pnas.2310080121. URL <https://pnas.org/doi/10.1073/pnas.2310080121>.
- [12] Tarik Benmarhnia, Nicole A. Errett, and Joan A. Casey. Beneath the smoke: Understanding the public health impacts of the Los Angeles urban wildfires. *Environmental Epidemiology*, 9(3):e388, June 2025. doi: 10.1097/EE9.0000000000000388.
- [13] OAR US EPA. Wildfire Smoke - A Complex Mixture, August 2025. URL <https://www.epa.gov/wildfire-smoke-course/wildfire-smoke-complex-mixture>.
- [14] Weizhi Deng, Jun Wang, Meng Zhou, Xi Chen, Xiaodong Wu, Huanxin Zhang, Jason B. Cohen, Jing Wei, Arlindo da Silva, Guy P. Brasseur, Claire Granier, and Laurence Rouil. Fires reverse progress toward ozone air quality standards in the United States. *Science*, 392(6802):1088–1092, June 2026. doi: 10.1126/science.aed3197. URL <https://www.science.org/doi/10.1126/science.aed3197>.
- [15] US Environmental Protection Agency. Integrated science assessment (ISA) for particulate

- matter. Final Report EPA/600/R-19/188, US Environmental Protection Agency, Washington DC, 2019. URL <https://assessments.epa.gov/isa/document/&deid=347534>.
- [16] Carlos F Gould, Sam Heft-Neal, Mary Johnson, Juan Aguilera, Marshall Burke, and Kari Nadeau. Health effects of wildfire smoke exposure. *Annual Review of Medicine*, 75(1): 277–292, 2024.
- [17] 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, 2019.
- [18] Joan A Casey, Marianthi-Anna Kioumourtzoglou, Amy Padula, David JX González, Holly Elser, Rosana Aguilera, Alexander J Northrop, Sara Y Tartof, Elizabeth Rose Mayeda, Danielle Braun, and others. Measuring long-term exposure to wildfire PM_{2.5} in California: Time-varying inequities in environmental burden. *Proceedings of the National Academy of Sciences*, 121(8):e2306729121, 2024.
- [19] Joan A. Casey, Yuqian M. Gu, Lara Schwarz, Timothy B. Frankland, Lauren B. Wilner, Heather McBrien, Nina M. Flores, Arnab K. Dey, Gina S. Lee, Chen Chen, Tarik Benmarhnia, and Sara Y. Tartof. The 2025 Los Angeles Wildfires and Outpatient Acute Health Care Utilization. *JAMA Health Forum*, 6(11):e254632, November 2025. ISSN 2689-0186. doi: 10.1001/jamahealthforum.2025.4632. URL <https://doi.org/10.1001/jamahealthforum.2025.4632>.
- [20] V. Do, C. Chen, T. Benmarhnia, and J. A. Casey. Spatial Heterogeneity of the Respiratory Health Impacts of Wildfire Smoke PM_{2.5} in California. *Geo-Health*, 8(4):e2023GH000997, 2024. ISSN 2471-1403. doi: 10.1029/2023GH000997. URL <https://onlinelibrary.wiley.com/doi/abs/10.1029/2023GH000997>. _eprint: <https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2023GH000997>.
- [21] Rosana Aguilera, Thomas Corringham, Alexander Gershunov, and Tarik Benmarhnia. Wild-fire smoke impacts respiratory health more than fine particles from other sources: observational evidence from Southern California. *Nature communications*, 12(1):1493, 2021.

- [22] 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, September 2016. ISSN 0091-6765. doi: 10.1289/ehp.1409277. URL <https://pmc.ncbi.nlm.nih.gov/articles/PMC5010409/>.
- [23] Marshall Burke, Sam Heft-Neal, Jessica Li, Anne Driscoll, Patrick Baylis, Matthieu Stigler, Joakim A. Weill, Jennifer A. Burney, Jeff Wen, Marissa L. Childs, and Carlos F. Gould. Exposures and behavioural responses to wildfire smoke. *Nature Human Behaviour*, 6(10): 1351–1361, October 2022. ISSN 2397-3374. doi: 10.1038/s41562-022-01396-6.
- [24] Annie I Chen, Keita Ebisu, Tarik Benmarhnia, and Rupa Basu. Emergency department visits associated with wildfire smoke events in California, 2016–2019. *Environmental Research*, 238:117154, 2023.
- [25] Wenhao Wang, Linzi Li, Qingyang Zhu, Rohan Richard D’Souza, Danlu Zhang, Haisu Zhang, Stefanie Ebel, Howard H Chang, Alvaro Alonso, and Yang Liu. Differential effects of wildfire smoke pm_{2.5} exposure on respiratory disease emergency department visits in the western united states. *American Journal of Respiratory and Critical Care Medicine*, (ja), 2025.
- [26] Youn Soo Jung, Mary M Johnson, Marshall Burke, Sam Heft-Neal, Melissa L Bondy, R Sharon Chinthrajah, Mark R Cullen, Lorene Nelson, Caleb Dresser, and Kari C Nadeau. Fine particulate matter from 2020 California wildfires and mental health–related emergency department visits. *JAMA Network Open*, 8(4):e253326–e253326, 2025.
- [27] Zachary S Wettstein and Ambarish Vaidyanathan. Psychotropic medication prescriptions and large California wildfires. *JAMA network open*, 7(2):e2356466–e2356466, 2024.
- [28] Stephanie E. Cleland, Lauren H. Wyatt, Linda Wei, Naman Paul, Marc L. Serre, J. Jason West, Sarah B. Henderson, and Ana G. Rappold. Short-Term Exposure to Wildfire Smoke and PM_{2.5} and Cognitive Performance in a Brain-Training Game: A Longitudinal Study of U.S. Adults. *Environmental Health Perspectives*, 130(6):067005, June 2022. ISSN 0091-6765, 1552-9924. doi: 10.1289/EHP10498. URL <https://ehp.niehs.nih.gov/doi/10.1289/EHP10498>.

- [29] Patricia To, Ejemai Eboreime, and Vincent IO Agyapong. The impact of wildfires on mental health: a scoping review. *Behavioral Sciences*, 11(9):126, 2021.
- [30] Holly Elser, Timothy B Frankland, Chen Chen, Sara Y Tartof, Elizabeth Rose Mayeda, Gina S Lee, Alexander J Northrop, Jacqueline M Torres, Tarik Benmarhnia, and Joan A Casey. Wildfire smoke exposure and incident dementia. *JAMA neurology*, 82(1):40–48, 2025.
- [31] Yiqun Ma, Emma Zang, Yang Liu, Jing Wei, Yuan Lu, Harlan M. Krumholz, Michelle L. Bell, and Kai Chen. Long-term exposure to wildland fire smoke PM_{2.5} and mortality in the contiguous United States. *Proceedings of the National Academy of Sciences*, 121(40): e2403960121, October 2024. ISSN 0027-8424, 1091-6490. doi: 10.1073/pnas.2403960121. URL <https://pnas.org/doi/10.1073/pnas.2403960121>.
- [32] Sara Hamideh, Payel Sen, and Erica Fischer. Wildfire impacts on education and healthcare: Paradise, california, after the camp fire. *Natural hazards*, pages 1–35, 2022.
- [33] Rosana Aguilera, Andrew Nakamura, Thomas Corringham, and Tarik Benmarhnia. Motor Vehicle Crashes during Wildfire Smoke Events in California (2010-2020).
- [34] H McBrien, ST Rowland, T Benmarhnia, SY Tartof, B Steiger, and JA Casey. Wildfire exposure and health care use among people who use durable medical equipment in southern california. *Epidemiology (Cambridge, Mass.)*, 34(5):700–711, September 2023. doi: 10.1097/EDE.0000000000001634.
- [35] Sophia D. Arabadjis, Stuart H. Sweeney, Catelynn E. Kenner, and Dominic J. Tedesco. Wildfire, evacuation, and cardiovascular events: A spatial exposure approach. *Applied Geography*, 159:103033, October 2023. ISSN 01436228. doi: 10.1016/j.apgeog.2023.103033. URL <https://linkinghub.elsevier.com/retrieve/pii/S0143622823001649>.
- [36] Syeda Narmeen Zehra and Stephen D. Wong. Systematic review and research gaps on wildfire evacuations: infrastructure, transportation modes, networks, and planning. *Transportation Planning and Technology*, 47(8):1364–1398, November 2024. ISSN 0308-1060. doi: 10.1080/03081060.2024.2348713. URL <https://doi.org/10.1080/03081060.2024.2348713>. _eprint: <https://doi.org/10.1080/03081060.2024.2348713>.

- [37] Joan A Casey, Mihoka Fukurai, Diana Hernández, Satchit Balsari, and Mathew V Kiang. Power outages and community health: a narrative review. *Current environmental health reports*, 7:371–383, 2020.
- [38] Alexander J Northrop, Nina M Flores, Vivian Do, Perry E Sheffield, and Joan A Casey. Power outages and pediatric unintentional injury hospitalizations in New York State. *Environmental Epidemiology*, 8(1):e287, 2024.
- [39] Shao Lin, Wangjian Zhang, Scott Sheridan, Melanie Mongillo, Stephen DiRienzo, Neil A Stuart, Eric K Stern, Guthrie Birkhead, Guanghui Dong, Shaowei Wu, and others. The immediate effects of winter storms and power outages on multiple health outcomes and the time windows of vulnerability. *Environmental Research*, 196:110924, 2021.
- [40] Brian Stone Jr, Carina J Gronlund, Evan Mallen, David Hondula, Marie S O’Neill, Mayuri Rajput, Santiago Grijalva, Kevin Lanza, Sharon Harlan, Larissa Larsen, and others. How blackouts during heat waves amplify mortality and morbidity risk. *Environmental Science & Technology*, 57(22):8245–8255, 2023.
- [41] Zhihu Xu, Rongbin Xu, Gongbo Chen, Wenzhong Huang, Zhengyu Yang, Wenhua Yu, Yuan Gao, Yao Wu, Yiwen Zhang, Pei Yu, Shuang Zhou, Bo Wen, Ke Ju, Kathryn Haden, Emily Nehme, Shanshan Li, and Yuming Guo. Power outages increase the risk of ambulance attendances associated with non-optimal temperatures. *Environmental Research*, 285:122396, November 2025. ISSN 00139351. doi: 10.1016/j.envres.2025.122396. URL <https://linkinghub.elsevier.com/retrieve/pii/S0013935125016470>.
- [42] Vivian Do Heather McBrien, Daniel Mork. Power outages and cardiovascular and respiratory hospitalizations among US older adults. *Nature*, 2025.
- [43] Noelle Angelique M Molinari, Bei Chen, Nevin Krishna, and Thomas Morris. Who’s at risk when the power goes out? The at-home electricity-dependent population in the United States, 2012. *Journal of public health management and practice*, 23(2):152–159, 2017.
- [44] Joseph W. Mitchell. Power line failures and catastrophic wildfires under extreme weather conditions. *Engineering Failure Analysis*, 35:726–735, December 2013. ISSN 13506307. doi:

- 10.1016/j.engfailanal.2013.07.006. URL <https://linkinghub.elsevier.com/retrieve/pii/S1350630713002343>.
- [45] Claire Miller, Matt Plucinski, Andrew Sullivan, Alec Stephenson, Carolyn Huston, Kay Charman, Mahesh Prakash, and Simon Dunstall. Electrically caused wildfires in Victoria, Australia are over-Represented when fire danger is elevated. *Landscape and Urban Planning*, 167: 267–274, November 2017. ISSN 0169-2046. doi: 10.1016/j.landurbplan.2017.06.016. URL <https://www.sciencedirect.com/science/article/pii/S0169204617301548>.
- [46] Vivian Do, Lauren B Wilner, Nina M Flores, Heather McBrien, Alexander J Northrop, and Joan A Casey. Spatiotemporal patterns of individual and multiple simultaneous severe weather events co-occurring with power outages in the United States, 2018–2020. *PLOS Climate*, 4(1):e0000523, 2025.
- [47] Bo Wang, Han Shi, Yueming ‘Lucy’ Qiu, Nana Deng, Destenie Nock, Xingchi Shen, Zhao-hua Wang, and Yi ‘David’ Wang. Unequal power outages induced by natural disasters. *Nature Communications*, 16(1):8947, October 2025. ISSN 2041-1723. doi: 10.1038/s41467-025-64012-x. URL <https://www.nature.com/articles/s41467-025-64012-x>.
- [48] Milo Gordon, Benjamin B Stieger, Alexander J Northrop, Heather McBrien, Brittany Shea, Gabriella Y Meltzer, Neil Singh Bedi, Elizabeth M Blake, Lauren B Wilner, Logan Piepmeier, Tarik Benmarhnia, Danielle Braun, and Joan A Casey. Two decades of United States wildfire burn zone disaster data, 2000-2019. *Nature*, 2025.
- [49] California Public Utilities Commission. Public safety power shutoffs (PSPS), 2025. URL <https://www.cpuc.ca.gov/consumer-support/psps>.
- [50] Weiwei Xie and Qingmin Meng. Social vulnerability analysis of planned power outages: A spatial study of power outage in California caused by wildfire risk. *Sustainable Cities and Society*, 120:106163, February 2025. ISSN 22106707. doi: 10.1016/j.scs.2025.106163. URL <https://linkinghub.elsevier.com/retrieve/pii/S2210670725000411>.
- [51] Vivian Do, Heather McBrien, Nina M Flores, Alexander J Northrop, Jeffrey Schlegelmilch, Mathew V Kiang, and Joan A Casey. Spatiotemporal distribution of power outages with

- climate events and social vulnerability in the USA. *Nature communications*, 14(1):2470, 2023.
- [52] Adam X Andresen, Liza C Kurtz, David M Hondula, Sara Meerow, and Melanie Gall. Understanding the social impacts of power outages in North America: a systematic review. *Environmental Research Letters*, 18(5):053004, 2023.
- [53] Can Huang, Qinran Hu, Linwei Sang, Donald D Lucas, Robin Wong, Bin Wang, Wanshi Hong, Mengqi Yao, and Vaibhav Donde. A review of public safety power shutoffs (PSPS) for wildfire mitigation: Policies, practices, models and data sources. *IEEE Transactions on Energy Markets, Policy and Regulation*, 1(3):187–197, 2023.
- [54] Jason Sacks. Informing public health protection under new patterns of wildfire smoke. URL <https://www.pnas.org/doi/10.1073/pnas.2418529121>.
- [55] Jason D. Sacks, Christopher T. Migliaccio, Colleen E. Reid, and Luke Montrose. Shifting the Conversation on Wildland Fire Smoke Exposures: More Smoke Within and Across Years Requires a New Approach to Inform Public Health Action. *ACS ES&T air*, 2(2):122–129, February 2025. ISSN 2837-1402. doi: 10.1021/acsestair.4c00236. URL <https://pmc.ncbi.nlm.nih.gov/articles/PMC11964113/>.
- [56] Stephanie E. Cleland, Olivia Pearl Xi-Qiong Hamilton, Michael Brauer, and Sarah B. Henderson. Multiyear wildfire smoke exposure (MultiWiSE) metrics: a data-driven approach to characterizing episodic PM_{2.5} exposures for epidemiologic research. *Journal of Exposure Science & Environmental Epidemiology*, pages 1–11, April 2026. ISSN 1559-064X. doi: 10.1038/s41370-026-00876-5. URL <https://www.nature.com/articles/s41370-026-00876-5>.
- [57] Peter Craig, Srinivasa Vittal Katikireddi, Alastair Leyland, and Frank Popham. Natural Experiments: An Overview of Methods, Approaches, and Contributions to Public Health Intervention Research. *Annual Review of Public Health*, 38(1):39–56, March 2017. ISSN 0163-7525, 1545-2093. doi: 10.1146/annurev-publhealth-031816-044327. URL <https://www.annualreviews.org/doi/10.1146/annurev-publhealth-031816-044327>.

- [58] Coady Wing, Kosali Simon, and Ricardo A. Bello-Gomez. Designing Difference in Difference Studies: Best Practices for Public Health Policy Research. *Annual Review of Public Health*, 39(1):453–469, April 2018. ISSN 0163-7525, 1545-2093. doi: 10.1146/annurev-publhealth-040617-013507. URL <https://www.annualreviews.org/content/journals/10.1146/annurev-publhealth-040617-013507>.
- [59] William Shadish, Thomas Cook, and Donald Campbell. *EXPERIMENTAL AND QUASI-EXPERIMENTAL DESIGNS FOR GENERALIZED CAUSAL INFERENCE*. HOUGHTON-MIFFLINCOMPAN, 2002.
- [60] Roch A Nianogo, Tarik Benmarhnia, and Stephen O'Neill. A comparison of quasi-experimental methods with data before and after an intervention: an introduction for epidemiologists and a simulation study. *International Journal of Epidemiology*, 52(5):1522–1533, October 2023. ISSN 0300-5771, 1464-3685. doi: 10.1093/ije/dyad032. URL <https://academic.oup.com/ije/article/52/5/1522/7110226>.
- [61] Arnab K Dey, Yiqun Ma, Gabriel Carrasco-Escobar, Changwoo Han, François Rerolle, and Tarik Benmarhnia. Two-stage interrupted time series analysis with machine learning: evaluating the health effects of the 2018 wildfire smoke event in San Francisco County as a case study. *American Journal of Epidemiology*, 194(10):2936–2944, July 2025. ISSN 0002-9262. doi: 10.1093/aje/kwaf147. URL <https://pmc.ncbi.nlm.nih.gov/articles/PMC12527249/>.
- [62] Heather McBrien, Daniel Mork, Marianthi-Anna Kioumourtzoglou, and Joan A Casey. Assessing bias in measuring power outage exposure with simulations. *Environmental Epidemiology*, 9(4):e403, 2025.
- [63] Joan A. Casey, Marriele Mango, Seth Mullendore, Mathew V. Kiang, Diana Hernández, Bonnie H. Li, Kris Li, Theresa M. Im, and Sara Y. Tartof. Trends from 2008 to 2018 in Electricity-dependent Durable Medical Equipment Rentals and Sociodemographic Disparities. *Epidemiology*, 32(3):327–335, May 2021. ISSN 1044-3983. doi: 10.1097/EDE.0000000000001333. URL <https://journals.lww.com/10.1097/EDE.0000000000001333>.

- [64] Miguel A. Hernán, Sonia Hernández-Díaz, and James M. Robins. A Structural Approach to Selection Bias:. *Epidemiology*, 15(5):615–625, September 2004. ISSN 1044-3983. doi: 10.1097/01.ede.0000135174.63482.43. URL <http://journals.lww.com/00001648-200409000-00020>.
- [65] Timothy L. Lash, Tyler J. VanderWeele, Sebastien Haneuse, and Kenneth J. Rothman. *Modern Epidemiology*. Wolters Kluwer, 4th edition, 2021. ISBN 978-1-4511-9328-2.
- [66] Miguel A Hernan and James M Robins. *Causal Inference: What If*. 2025.
- [67] Chanelle J. Howe, Stephen R. Cole, Bryan Lau, Sonia Napravnik, and Joseph J. Eron. Selection Bias Due to Loss to Follow Up in Cohort Studies:. *Epidemiology*, 27(1):91–97, January 2016. ISSN 1044-3983. doi: 10.1097/EDE.0000000000000409. URL <http://journals.lww.com/00001648-201601000-00014>.
- [68] Alberto Abadie, Alexis Diamond, and Jens Hainmueller. Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California’s Tobacco Control Program. *Journal of the American Statistical Association*, 105(490):493–505, June 2010. ISSN 0162-1459, 1537-274X. doi: 10.1198/jasa.2009.ap08746. URL <http://www.tandfonline.com/doi/abs/10.1198/jasa.2009.ap08746>.
- [69] Yinka Oyelese. Randomized controlled trials: not always the “gold standard” for evidence in obstetrics and gynecology. *American Journal of Obstetrics and Gynecology*, 230(4): 417–425, April 2024. ISSN 00029378. doi: 10.1016/j.ajog.2023.10.015. URL <https://linkinghub.elsevier.com/retrieve/pii/S0002937823007457>.
- [70] Laura E. Bothwell, Jeremy A. Greene, Scott H. Podolsky, and David S. Jones. Assessing the Gold Standard — Lessons from the History of RCTs. *New England Journal of Medicine*, 374(22):2175–2181, June 2016. ISSN 0028-4793, 1533-4406. doi: 10.1056/NEJMms1604593. URL <http://www.nejm.org/doi/10.1056/NEJMms1604593>.
- [71] Justin B. Dimick and Andrew M. Ryan. Methods for Evaluating Changes in Health Care Policy: The Difference-in-Differences Approach. *JAMA*, 312(22):2401, December 2014. ISSN

- 0098-7484. doi: 10.1001/jama.2014.16153. URL <http://jama.jamanetwork.com/article.aspx?doi=10.1001/jama.2014.16153>.
- [72] Malcolm Maclure. The case-crossover design: a method for studying transient effects on the risk of acute events. *American journal of epidemiology*, 133(2):144–153, 1991.
- [73] Holly Janes, Lianne Sheppard, and Thomas Lumley. Case–crossover analyses of air pollution exposure data: referent selection strategies and their implications for bias. *Epidemiology (Cambridge, Mass.)*, 16(6):717–726, 2005.
- [74] James Lopez Bernal, Steven Cummins, and Antonio Gasparrini. Interrupted time series regression for the evaluation of public health interventions: a tutorial. *International Journal of Epidemiology*, page dyw098, June 2016. ISSN 0300-5771, 1464-3685. doi: 10.1093/ije/dyw098. URL <https://academic.oup.com/ije/article-lookup/doi/10.1093/ije/dyw098>.
- [75] Eduardo Carracedo-Martinez, Margarita Taracido, Aurelio Tobias, Marc Saez, and Adolfo Figueiras. Case-crossover analysis of air pollution health effects: a systematic review of methodology and application. *Environmental health perspectives*, 118(8):1173–1182, 2010.
- [76] Thomas Lumley and Drew Levy. Bias in the case–crossover design: implications for studies of air pollution. *Environmetrics: The Official Journal of the International Environmetrics Society*, 11(6):689–704, 2000.
- [77] James Lopez Bernal, Steven Cummins, and Antonio Gasparrini. The use of controls in interrupted time series studies of public health interventions. *International Journal of Epidemiology*, 47(6):2082–2093, December 2018. ISSN 0300-5771, 1464-3685. doi: 10.1093/ije/dyy135. URL <https://academic.oup.com/ije/article/47/6/2082/5049576>.
- [78] E. Kontopantelis, T. Doran, D. A. Springate, I. Buchan, and D. Reeves. Regression based quasi-experimental approach when randomisation is not an option: interrupted time series analysis. *BMJ*, 350(jun09 5):h2750–h2750, June 2015. ISSN 1756-1833. doi: 10.1136/bmj.h2750. URL <https://www.bmj.com/lookup/doi/10.1136/bmj.h2750>.

- [79] Yiqun Ma and Tarik Benmarhnia. Interrupted Time Series Analysis in Environmental Epidemiology: A Review of Traditional and Novel Modeling Approaches. *Current Environmental Health Reports*, 12(1):50, December 2025. ISSN 2196-5412. doi: 10.1007/s40572-025-00517-3. URL <https://link.springer.com/10.1007/s40572-025-00517-3>.
- [80] Jonathan M Snowden. Advancing epidemiological methods: from innovation to communication. *International Journal of Epidemiology*, 53(4):dyae107, June 2024. ISSN 1464-3685. doi: 10.1093/ije/dyae107. URL <https://academic.oup.com/ije/article/doi/10.1093/ije/dyae107/7731164>.
- [81] Roman Hornung, László Németh, Oleksandr Zadorozhnyi, Theresa Ullmann, Michael Kammer, Rebecca Killick, Christopher Paciorek, Julien Chiquet, Moritz Herrmann, Lucija Batinović, Rickard Carlsson, Pierre Neuvial, Boris Hejblum, Julia Wrobel, Anne-Laure Boulesteix, and Karsten Tabelow. Overcoming barriers to computational reproducibility.
- [82] Victoria Stodden, Marcia McNutt, David H. Bailey, Ewa Deelman, Yolanda Gil, Brooks Hanson, Michael A. Heroux, John P.A. Ioannidis, and Michela Taufer. Enhancing reproducibility for computational methods. *Science*, 354(6317):1240–1241, December 2016. ISSN 0036-8075, 1095-9203. doi: 10.1126/science.aah6168. URL <https://www.science.org/doi/10.1126/science.aah6168>.
- [83] PSE Healthy Energy. Public safety power shutoffs explained, 2024. URL <https://www.psehealthyenergy.org/public-safety-power-shutoffs-explained/>.
- [84] California Public Utilities Commission. Utility company PSPS reports: Post-event, post-season and pre-season. URL <https://www.cpuc.ca.gov/consumer-support/pmps/utility-company-pmps-reports-post-event-and-post-season>.
- [85] Gershunov Aguilera, R. and P. D. Sampson. A novel ensemble-based statistical approach to estimate daily wildfire-specific PM_{2.5} in California (2006–2020). *Environment International*, 171:107719, 2023. doi: 10.1016/j.envint.2022.107719.
- [86] California Health Care Access and Information. HCAI data datasets. URL <https://hcai.ca.gov/data/datasets/>.

- [87] Imtiaj Khan and Mona Ghassemi. A probabilistic approach for analysis of line outage risk caused by wildfires. *International Journal of Electrical Power & Energy Systems*, 139:108042, 2022.
- [88] Alyson B. Harding, Gillian A.M. Tarr, Jesse D. Berman, Darin J. Erickson, and Marizen R. Ramirez. The association of Public Safety Power Shutoffs and motor vehicle crashes. *Journal of Safety Research*, 93:148–155, July 2025. ISSN 00224375. doi: 10.1016/j.jsr.2025.02.001. URL <https://linkinghub.elsevier.com/retrieve/pii/S0022437525000180>.
- [89] California Public Utilities Commission. 2025 senate bill 695 report: Report to the governor and legislature on actions to limit utility cost and rate increases pursuant to public utilities code section 913.1. Report, California Public Utilities Commission, September 2025.
- [90] U.S. Energy Information Administration. Electricity data browser: Sales, revenue and price, 2025. URL https://www.eia.gov/electricity/sales_revenue_price/.
- [91] Nicholas J. Depsky, Lara Cushing, and Rachel Morello-Frosch. High-resolution gridded estimates of population sociodemographics from the 2020 census in California. *PLOS ONE*, 17(7):e0270746, 2022. doi: 10.1371/journal.pone.0270746. URL <https://doi.org/10.1371/journal.pone.0270746>.
- [92] Shawn D Aaron, Gavin C Donaldson, George A Whitmore, John R Hurst, Tim Ramsay, and Jadwiga A Wedzicha. Time course and pattern of COPD exacerbation onset. *Thorax*, 67(3): 238–243, 2012.
- [93] John T Abatzoglou. Development of gridded surface meteorological data for ecological applications and modelling. *International journal of climatology*, 33(1):121–131, 2013.
- [94] Lisa Yamasaki, Takuma Kamada, Chris Fook Sheng Ng, Yuya Takane, Ko Nakajima, Kazuki Yamaguchi, Kazutaka Oka, Yasushi Honda, Yoonhee Kim, and Masahiro Hashizume. Heat-related mortality and ambulance transport after a power outage in the Tokyo metropolitan area. *Environmental Epidemiology*, 8(2):e292, April 2024. ISSN 2474-7882. doi: 10.1097/EE9.0000000000000292. URL <https://journals.lww.com/10.1097/EE9.0000000000000292>.

- [95] Shao Lin, Barbara A Fletcher, Ming Luo, Robert Chinery, and Syni-An Hwang. Health impact in new york city during the northeastern blackout of 2003. *Public Health Reports*, 126(3): 384–393, 2011.
- [96] Shao Lin, Quan Qi, Han Liu, Xinlei Deng, Ian Trees, Xiaojun Yuan, and Mary P Gallant. The joint effects of thunderstorms and power outages on respiratory-related emergency visits and modifying and mediating factors of this relationship. *Environmental Health Perspectives*, 132(6):067002, 2024.
- [97] Wangjian Zhang, Scott C. Sheridan, Guthrie S. Birkhead, Daniel P. Croft, Jerald A. Brotzge, John G. Justino, Neil A. Stuart, Zhicheng Du, Xiaobo X. Romeiko, Bo Ye, Guanghui Dong, Yuantao Hao, and Shao Lin. Power Outage. *Chest*, 158(6):2346–2357, December 2020. ISSN 00123692. doi: 10.1016/j.chest.2020.05.555. URL <https://linkinghub.elsevier.com/retrieve/pii/S0012369220316202>.
- [98] Vivian Do, Heather Kathleen McBrien, Donald Edmondson, Marianthi-Anna Kioumourtoglou, and Joan Allison Casey. The impact of power outages on cardiovascular hospitalizations among medicare fee-for-service enrollees in new york state, 2017–2018. *Epidemiology (Cambridge, Mass.)*, 36(4):458–466, 2025.
- [99] Christine Dominianni, Kathryn Lane, Sarah Johnson, Kazuhiko Ito, and Thomas Matte. Health impacts of citywide and localized power outages in New York City. *Environmental Health Perspectives*, 126(6):067003, 2018.
- [100] Xinlei Deng, Samantha Friedman, Ian Ryan, Wangjian Zhang, Guanghui Dong, Havidan Rodriguez, Fangqun Yu, Wenzhong Huang, Arshad Nair, Gan Luo, and others. The independent and synergistic impacts of power outages and floods on hospital admissions for multiple diseases. *Science of the total environment*, 828:154305, 2022.
- [101] Abdallah Ibrahim, Genevieve Cecilia Aryeetey, Emmanuel Asampong, Duah Dwomoh, and Justice Nonvignon. Erratic electricity supply (Dumsor) and anxiety disorders among university students in Ghana: a cross sectional study. *International journal of mental health systems*, 10:1–9, 2016.

- [102] Gabrielle Wong-Parodi. Support for public safety power shutoffs in California: Wildfire-related perceived exposure and negative outcomes, prior and current health, risk appraisal and worry. *Energy Research & Social Science*, 88:102495, 2022. ISSN 2214-6296. doi: 10.1016/j.erss.2022.102495. URL <https://www.sciencedirect.com/science/article/pii/S2214629622000032>.
- [103] Scott C Sheridan, Wangjian Zhang, Xinlei Deng, and Shao Lin. The individual and synergistic impacts of windstorms and power outages on injury ED visits in New York State. *Science of the total environment*, 797:149199, 2021.
- [104] Michael W Hess. Oxygen therapy in COPD. *Respiratory Care*, 68(7):998–1012, 2023.
- [105] Shawn PE Nishi, Wei Zhang, Yong-Fang Kuo, and Gulshan Sharma. Oxygen therapy use in older adults with chronic obstructive pulmonary disease. *PloS one*, 10(3):e0120684, 2015.
- [106] Yanji Qu, Wangjian Zhang, Bo Ye, Samantha Penta, Guanghui Dong, Xiaoqing Liu, and Shao Lin. Power outage mediates the associations between major storms and hospital admission of chronic obstructive pulmonary disease. *BMC Public health*, 21(1):1961, 2021.
- [107] Centers for Disease Control and Prevention. State estimates of COPD, May 2024. URL <https://www.cdc.gov/copd/php/case-reporting/state-level-estimates-of-copd.html>.
- [108] E Rand Sutherland, Barry J Make, Sverre Vedal, Lening Zhang, Steven J Dutton, James R Murphy, and Philip E Silkoff. Wildfire smoke and respiratory symptoms in patients with chronic obstructive pulmonary disease. *Journal of Allergy and Clinical Immunology*, 115(2):420–422, 2005.
- [109] May-Lin Wilgus and Maryum Merchant. Clearing the air: understanding the impact of wildfire smoke on asthma and COPD. In *Healthcare*, volume 12, page 307. MDPI, 2024. Number: 3.
- [110] GB Anderson and ML Bell. Impacts of the august 2003 power outage on mortality in new york, ny. In *American journal of epidemiology*, volume 173, pages S98–S98. OXFORD UNIV PRESS INC JOURNALS DEPT, 2001 EVANS RD, CARY, NC 27513 USA, 2011.

- [111] Julianne Skarha, Lily Gordon, Nazmus Sakib, Joseph June, Dylan J Jester, Lindsay J Peterson, Ross Andel, and David M Dosa. Association of power outage with mortality and hospitalizations among Florida nursing home residents after Hurricane Irma. In *JAMA health forum*, volume 2, pages e213900–e213900. American Medical Association, 2021. Number: 11.
- [112] California Hospital Association. Public safety power shutoff: Assessment and recommendations. Technical report, California Hospital Association, November 2019. URL https://calhospital.org/wp-content/uploads/2019/11/psps_doc_final.pdf.
- [113] Climate Central. Weather-related power outages rising, 2024. URL <https://www.climatecentral.org/climate-matters/weather-related-power-outages-rising>.
- [114] Attila J Hertelendy, Jeremy Maggin, and Gregory R Ciottone. Health-care system adaptability during wildfire disasters: crucial insights from LA County. *The Lancet*, 405(10479):621–622, February 2025. ISSN 01406736. doi: 10.1016/S0140-6736(25)00241-7. URL <https://linkinghub.elsevier.com/retrieve/pii/S0140673625002417>.
- [115] Orison O. Woolcott. Los Angeles County in flames: responsibilities on fire. *The Lancet Regional Health - Americas*, 42:101005, February 2025. ISSN 2667193X. doi: 10.1016/j.lana.2025.101005. URL <https://linkinghub.elsevier.com/retrieve/pii/S2667193X25000158>.
- [116] Claire Schollaert, Rachel Connolly, Lara Cushing, Michael Jerrett, Tianjia Liu, and Miriam Marlier. Air Quality Impacts of the January 2025 Los Angeles Wildfires: Insights from Public Data Sources. *Environmental Science & Technology Letters*, 12(8):911–917, August 2025. ISSN 2328-8930, 2328-8930. doi: 10.1021/acs.estlett.5c00486. URL <https://pubs.acs.org/doi/10.1021/acs.estlett.5c00486>.
- [117] Eugenio Paglino, Rafeya V. Raquib, and Andrew C. Stokes. Excess Deaths Attributable to the Los Angeles Wildfires From January 5 to February 1, 2025. *JAMA*, 334(11):1018–1019, September 2025. ISSN 0098-7484. doi: 10.1001/jama.2025.10556. URL <https://doi.org/10.1001/jama.2025.10556>.

- [118] Joseph E. Ebinger, Tzu Yu Huang, Sandy Y. Joung, Juliane Louise F. Kwong, Wasay Warsi, Nancy Sun, Jesse Navarrette, Patrick Botting, Zaldy S. Tan, Brian L. Claggett, Alan C. Kwan, and Susan Cheng. Emergency Encounters for Illness During and After the Los Angeles Wildfires. *JACC*, page S0735109725101678, December 2025. ISSN 07351097. doi: 10.1016/j.jacc.2025.10.079. URL <https://linkinghub.elsevier.com/retrieve/pii/S0735109725101678>.
- [119] Emily Kajita. Notes from the Field: Emergency Department Use During the Los Angeles County Wildfires, January 2025. *MMWR. Morbidity and Mortality Weekly Report*, 74, 2025. ISSN 0149-21951545-861X. doi: 10.15585/mmwr.mm7403a2. URL <https://www.cdc.gov/mmwr/volumes/74/wr/mm7403a2.htm>.
- [120] Glenn Rolph, Ariel Stein, and Barbara Stunder. Real-time Environmental Applications and Display sYstem: READY. *Environmental Modelling & Software*, 95:210–228, September 2017. ISSN 13648152. doi: 10.1016/j.envsoft.2017.06.025. URL <https://linkinghub.elsevier.com/retrieve/pii/S1364815217302360>.
- [121] A. F. Stein, R. R. Draxler, G. D. Rolph, B. J. B. Stunder, M. D. Cohen, and F. Ngan. NOAA's HYSPLIT Atmospheric Transport and Dispersion Modeling System. *Bulletin of the American Meteorological Society*, 96(12):2059–2077, December 2015. ISSN 0003-0007, 1520-0477. doi: 10.1175/BAMS-D-14-00110.1. URL <https://journals.ametsoc.org/doi/10.1175/BAMS-D-14-00110.1>.
- [122] Los Angeles County Department of Public Health. RESPWatch: Respiratory Illness Surveillance, 2025. URL <https://app.powerbigov.us/view?r=eyJrIjojMTY0MTcwOWItZDk4NS00ODBkLWUwNWItNDNlMjcyMDc3ZmQ2IiwidCI6IjA3NTk3MjQ4LWVhMzgtNDUxY>
- [123] Yiwen Zhang, Shuang Zhou, Rongbin Xu, Zhengyu Yang, Wenzhong Huang, Paulo H. N. Saldiva, Wenhua Yu, Gongbo Chen, Micheline S. Z. S. Coelho, Tingting Ye, Yanming Liu, Pei Yu, Eric Lavigne, Jiangning Song, Yuming Guo, and Shanshan Li. Wildfire-sourced fine particulate matter and mental disorders in children and adolescents. *Nature Mental Health*, 4(2):243–254, February 2026. ISSN 2731-6076. doi: 10.1038/s44220-025-00571-8. URL <https://www.nature.com/articles/s44220-025-00571-8>.

- [124] Vivian Do, Heather McBrien, Katharine Teigen, Marissa L. Childs, Marianthi-Anna Kioumourtzoglou, and Joan A. Casey. A National Study on the Impact of Wildfire Smoke on Cause-Specific Hospitalizations Among Medicare Enrollees with Alzheimer's Disease and Related Dementias from 2006 to 2016. *Fire*, 8(3):97, February 2025. ISSN 2571-6255. doi: 10.3390/fire8030097. URL <https://www.mdpi.com/2571-6255/8/3/97>.
- [125] Ryan Lee, Jennifer B. Unger, Daniel W. Soto, Eric Kawaguchi, Myles Cockburn, Shuvan Paul, and Frank Gilliland. Depression, Anxiety, and PTSD Among Southern California Residents After the January 2025 Los Angeles Wildfires. *Disaster Medicine and Public Health Preparedness*, 19:e327, 2025. ISSN 1935-7893, 1938-744X. doi: 10.1017/dmp.2025.10257.
- [126] Russell T. Jones, David P. Ribbe, and Phillippe Cunningham. Psychosocial correlates of fire disaster among children and adolescents. *Journal of Traumatic Stress*, 7(1):117–122, 1994. ISSN 1573-6598. doi: 10.1002/jts.2490070112. URL <https://onlinelibrary.wiley.com/doi/abs/10.1002/jts.2490070112>. _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1002/jts.2490070112>.
- [127] Sam Heft-Neal, Carlos F. Gould, Marissa L. Childs, Mathew V. Kiang, Kari C. Nadeau, Mark Duggan, Eran Bendavid, and Marshall Burke. Emergency department visits respond nonlinearly to wildfire smoke. *Proceedings of the National Academy of Sciences*, 120(39):e2302409120, September 2023. ISSN 0027-8424, 1091-6490. doi: 10.1073/pnas.2302409120. URL <https://pnas.org/doi/10.1073/pnas.2302409120>.
- [128] John R. Balmes, Anne Hicks, Mary M. Johnson, and Kari C. Nadeau. The Effect of Wildfires on Asthma and Allergies. *The Journal of Allergy and Clinical Immunology. In Practice*, 13(2): 280–287, February 2025. ISSN 2213-2201. doi: 10.1016/j.jaip.2024.12.004.
- [129] Lynne Jones, Joseph B Asare, Mustafa El Masri, Andrew Mohanraj, Hassen Sherief, and Mark Van Ommeren. Severe mental disorders in complex emergencies. *The Lancet*, 374(9690):654–661, August 2009. ISSN 01406736. doi: 10.1016/S0140-6736(09)61253-8. URL <https://linkinghub.elsevier.com/retrieve/pii/S0140673609612538>.
- [130] Philip S. Wang, Michael J. Gruber, Richard E. Powers, Michael Schoenbaum, Anthony H.

- Speier, Kenneth B. Wells, and Ronald C. Kessler. Disruption of Existing Mental Health Treatments and Failure to Initiate New Treatment After Hurricane Katrina. *American Journal of Psychiatry*, 165(1):34–41, January 2008. ISSN 0002-953X, 1535-7228. doi: 10.1176/appi.ajp.2007.07030502. URL <https://psychiatryonline.org/doi/10.1176/appi.ajp.2007.07030502>.
- [131] Geneviève Belleville, Marie-Christine Ouellet, Jessica Lebel, Sunita Ghosh, Charles M. Morin, Stéphane Bouchard, Stéphane Guay, Nicolas Bergeron, Tavis Campbell, and Frank P. MacMaster. Psychological Symptoms Among Evacuees From the 2016 Fort McMurray Wildfires: A Population-Based Survey One Year Later. *Frontiers in Public Health*, 9:655357, May 2021. ISSN 2296-2565. doi: 10.3389/fpubh.2021.655357. URL <https://www.frontiersin.org/articles/10.3389/fpubh.2021.655357/full>.
- [132] J. Lee Jenkins, Edbert B. Hsu, Lauren M. Sauer, Yu-Hsiang Hsieh, and Thomas D. Kirsch. Prevalence of Unmet Health Care Needs and Description of Health Care-seeking Behavior Among Displaced People After the 2007 California Wildfires. *Disaster Medicine and Public Health Preparedness*, 3(S1):S24–S28, June 2009. ISSN 1935-7893, 1938-744X. doi: 10.1097/DMP.0b013e31819f1afc.
- [133] Chittalsinh Raulji, Maria C. Velez, Pinki Prasad, Cierra Rousseau, and Renee V. Gardner. Impact of Hurricane Katrina on healthcare delivery for New Orleans patients, 2005–2014. *Pediatric Blood & Cancer*, 65(12):e27406, December 2018. ISSN 1545-5009, 1545-5017. doi: 10.1002/pbc.27406. URL <https://onlinelibrary.wiley.com/doi/10.1002/pbc.27406>.
- [134] Masafumi Nishizawa, Satoshi Hoshide, Masahisa Shimpo, and Kazuomi Kario. Disaster Hypertension: Experience from the Great East Japan Earthquake of 2011. *Current Hypertension Reports*, 14(5):375–381, October 2012. ISSN 1522-6417, 1534-3111. doi: 10.1007/s11906-012-0298-z. URL <http://link.springer.com/10.1007/s11906-012-0298-z>.
- [135] Andrew C. Miller and Bonnie Arquilla. Chronic Diseases and Natural Hazards: Impact of Disasters on Diabetic, Renal, and Cardiac Patients. *Prehospital and Disaster Medicine*, 23(2):185–194, April 2008. ISSN 1049-023X, 1945-1938. doi: 10.1017/S1049023X00005835.

- [136] Amesh A. Adalja, Matthew Watson, Nidhi Bouri, Kathleen Minton, Ryan C. Morhard, and Eric S. Toner. Absorbing Citywide Patient Surge During Hurricane Sandy: A Case Study in Accommodating Multiple Hospital Evacuations. *Annals of Emergency Medicine*, 64(1): 66–73.e1, July 2014. ISSN 0196-0644. doi: 10.1016/j.annemergmed.2013.12.010. URL <https://www.sciencedirect.com/science/article/pii/S0196064413016545>.
- [137] Sarah McCaffrey, Robyn Wilson, and Avishek Konar. Should I Stay or Should I Go Now? Or Should I Wait and See? Influences on Wildfire Evacuation Decisions. *Risk Analysis*, 38(7):1390–1404, July 2018. ISSN 0272-4332, 1539-6924. doi: 10.1111/risa.12944. URL <https://onlinelibrary.wiley.com/doi/10.1111/risa.12944>.
- [138] US Census Bureau. ACS Income Data Tables. URL <https://www.census.gov/topics/income-poverty/income/data/tables/acs.html>. Section: Government.
- [139] George C. Holzworth. *Mixing Heights, Wind Speeds, and Potential for Urban Air Pollution Throughout the Contiguous United States*. U.S. Government Printing Office, 1972. Google-Books-ID: JsFD_Hy36dkC.
- [140] Marcello Schiavina, Kytt J. MacManus, Sergio Freire, Alessandra Carioli, Chris Jacobs-Crisioni, Jip Claassens, Maarten Hilferink, and Lewis Dijkstra. GHS-WUP-POP R2025A – GHS-WUP population spatial raster dataset, derived from GHS-POP (R2023) and projected using the CRISP model, multitemporal (1975-2100). November 2025. doi: 10.2905/adba95af-db56-4569-acd3-9513201eba30. URL <http://data.europa.eu/89h/adba95af-db56-4569-acd3-9513201eba30>.
- [141] Marissa L. Childs, Jessica Li, Jeffrey Wen, Sam Heft-Neal, Anne Driscoll, Sherrie Wang, Carlos F. Gould, Minghao Qiu, Jennifer Burney, and Marshall Burke. Daily Local-Level Estimates of Ambient Wildfire Smoke PM_{2.5} for the Contiguous US. *Environmental Science & Technology*, 56(19):13607–13621, October 2022. ISSN 0013-936X. doi: 10.1021/acs.est.2c02934. URL <https://doi.org/10.1021/acs.est.2c02934>.
- [142] County of Los Angeles. Metadata Document, January 2025. URL <https://www.arcgis.com/sharing/rest/content/items/6241d8e277a541a2b3645947d991c35e/info/metadata/metadata.xml?format=default&output=html>.

- [143] Andrea L. Schaffer, Timothy A. Dobbins, and Sallie-Anne Pearson. Interrupted time series analysis using autoregressive integrated moving average (ARIMA) models: a guide for evaluating large-scale health interventions. *BMC Medical Research Methodology*, 21:58, March 2021. ISSN 1471-2288. doi: 10.1186/s12874-021-01235-8. URL <https://pmc.ncbi.nlm.nih.gov/articles/PMC7986567/>.
- [144] Katherine Baicker and Theodore Svoronos. NBER WORKING PAPER SERIES.
- [145] C Bottomley, M Ooko, A Gasparrini, and RH Keogh. In praise of Prais-Winsten: An evaluation of methods used to account for autocorrelation in interrupted time series. *Statistics in Medicine*, 42(8):1277–1288, April 2023. ISSN 0277-6715. doi: 10.1002/sim.9669. URL <https://pmc.ncbi.nlm.nih.gov/articles/PMC10946734/>.
- [146] Simon L. Turner, Andrew B. Forbes, Amalia Karahalios, Monica Taljaard, and Joanne E. McKenzie. Evaluation of statistical methods used in the analysis of interrupted time series studies: a simulation study. *BMC Medical Research Methodology*, 21:181, August 2021. ISSN 1471-2288. doi: 10.1186/s12874-021-01364-0. URL <https://pmc.ncbi.nlm.nih.gov/articles/PMC8403376/>.
- [147] Kenneth A Feder, Ramin Mojtabai, Elizabeth A Stuart, Rashelle Musci, and Elizabeth J Letourneau. Florida’s Opioid Crackdown and Mortality From Drug Overdose, Motor Vehicle Crashes, and Suicide: A Bayesian Interrupted Time-Series Analysis. *American Journal of Epidemiology*, 189(9):885–893, September 2020. ISSN 0002-9262, 1476-6256. doi: 10.1093/aje/kwaa015. URL <https://academic.oup.com/aje/article/189/9/885/5741085>.
- [148] Gareth James, Daniela Witten, Trevor Hastie, and Robert Tibshirani. *An Introduction to Statistical Learning*, volume 103 of *Springer Texts in Statistics*. Springer New York, New York, NY, 2013. ISBN 978-1-4614-7137-0 978-1-4614-7138-7. doi: 10.1007/978-1-4614-7138-7. URL <http://link.springer.com/10.1007/978-1-4614-7138-7>.
- [149] Gavin C Cawley and Nicola L C Talbot. On Over-fitting in Model Selection and Subsequent Selection Bias in Performance Evaluation.

- [150] Leonard J. Tashman. Out-of-sample tests of forecasting accuracy: an analysis and review. *International Journal of Forecasting*, 16(4):437–450, October 2000. ISSN 0169-2070. doi: 10.1016/S0169-2070(00)00065-0. URL <https://www.sciencedirect.com/science/article/pii/S0169207000000650>.
- [151] Christoph Bergmeir, Rob J. Hyndman, and Bonsoo Koo. A note on the validity of cross-validation for evaluating autoregressive time series prediction. *Computational Statistics & Data Analysis*, 120:70–83, April 2018. ISSN 01679473. doi: 10.1016/j.csda.2017.11.003. URL <https://linkinghub.elsevier.com/retrieve/pii/S0167947317302384>.
- [152] RJ Hyndman and G Athanasopoulos. *Forecasting: principles and practice*. URL [0Texts.com/fpp3](https://otexts.com/fpp3).
- [153] Vitor Cerqueira, Luis Torgo, and Igor Mozetič. Evaluating time series forecasting models: an empirical study on performance estimation methods. *Machine Learning*, 109(11):1997–2028, November 2020. ISSN 0885-6125, 1573-0565. doi: 10.1007/s10994-020-05910-7. URL <https://link.springer.com/10.1007/s10994-020-05910-7>.
- [154] Hans R. Kunsch. The Jackknife and the Bootstrap for General Stationary Observations. *The Annals of Statistics*, 17(3), September 1989. ISSN 0090-5364. doi: 10.1214/aos/1176347265. URL <https://projecteuclid.org/journals/annals-of-statistics/volume-17/issue-3/The-Jackknife-and-the-Bootstrap-for-General-Stationary-Observations/10.1214/aos/1176347265.full>.
- [155] S. S. SHAPIRO and M. B. WILK. An analysis of variance test for normality (complete samples). *Biometrika*, 52(3-4):591–611, December 1965. ISSN 0006-3444. doi: 10.1093/biomet/52.3-4.591. URL <https://doi.org/10.1093/biomet/52.3-4.591>.
- [156] Dimitris N. Politis and Halbert White. Automatic Block-Length Selection for the Dependent Bootstrap. *Econometric Reviews*, 23(1):53–70, December 2004. ISSN 0747-4938, 1532-4168. doi: 10.1081/ETC-120028836. URL <http://www.tandfonline.com/doi/abs/10.1081/ETC-120028836>.

- [157] Marina Romanello, Alice McGushin, Claudia Di Napoli, Paul Drummond, Nick Hughes, Louis Jamart, Harry Kennard, Pete Lampard, Baltazar Solano Rodriguez, Nigel Arnell, Sonja Ayeb-Karlsson, Kristine Belesova, Wenjia Cai, Diarmid Campbell-Lendrum, Stuart Capstick, Jonathan Chambers, Lingzhi Chu, Luisa Ciampi, Carole Dalin, Niheer Dasandi, Shouro Dasgupta, Michael Davies, Paula Dominguez-Salas, Robert Dubrow, Kristie L Ebi, Matthew Eckelman, Paul Ekins, Luis E Escobar, Lucien Georgeson, Delia Grace, Hilary Graham, Samuel H Gunther, Stella Hartinger, Kehan He, Clare Heaviside, Jeremy Hess, Shih-Che Hsu, Slava Jankin, Marcia P Jimenez, Ilan Kelman, Gregor Kiesewetter, Patrick L Kinney, Tord Kjellstrom, Dominic Kniveton, Jason K W Lee, Bruno Lemke, Yang Liu, Zhao Liu, Melissa Lott, Rachel Lowe, Jaime Martinez-Urtaza, Mark Maslin, Lucy McAllister, Celia McMichael, Zhifu Mi, James Milner, Kelton Minor, Nahid Mohajeri, Maziar Moradi-Lakeh, Karyn Morrissey, Simon Munzert, Kris A Murray, Tara Neville, Maria Nilsson, Nick Obradovich, Maquins Odhiambo Sewe, Tadj Oreszczyn, Matthias Otto, Fereidoon Owfi, Olivia Pearman, David Pencheon, Mahnaz Rabbaniha, Elizabeth Robinson, Joacim Rocklöv, Renee N Salas, Jan C Semenza, Jodi Sherman, Liuhua Shi, Marco Springmann, Meisam Tabatabaei, Jonathon Taylor, Joaquin Trinanes, Joy Shumake-Guillemot, Bryan Vu, Fabian Wagner, Paul Wilkinson, Matthew Winning, Marisol Yglesias, Shihui Zhang, Peng Gong, Hugh Montgomery, Anthony Costello, and Ian Hamilton. The 2021 report of the *Lancet* Countdown on health and climate change: code red for a healthy future. *The Lancet*, 398 (10311):1619–1662, October 2021. ISSN 0140-6736. doi: 10.1016/S0140-6736(21)01787-6. URL <https://www.sciencedirect.com/science/article/pii/S0140673621017876>.
- [158] Joan A. Casey, Robbie M. Parks, Tim A. Bruckner, Alison Gemmill, and Ralph Catalano. Excess Injury Mortality in Washington State During the 2021 Heat Wave. *American Journal of Public Health*, 113(6):657–660, June 2023. ISSN 0090-0036. doi: 10.2105/AJPH.2023.307269. URL <https://pmc.ncbi.nlm.nih.gov/articles/PMC10186831/>.
- [159] Robbie M. Parks, James E. Bennett, Helen Tamura-Wicks, Vasilis Kontis, Ralf Toumi, Goodarz Danaei, and Majid Ezzati. Anomalously warm temperatures are associated with increased injury deaths. *Nature Medicine*, 26(1):65–70, January 2020. ISSN 1078-8956,

- 1546-170X. doi: 10.1038/s41591-019-0721-y. URL <https://www.nature.com/articles/s41591-019-0721-y>.
- [160] Marshall Burke, Felipe González, Patrick Baylis, Sam Heft-Neal, Ceren Baysan, Sanjay Basu, and Solomon Hsiang. Higher temperatures increase suicide rates in the United States and Mexico. *Nature Climate Change*, 8(8):723–729, August 2018. ISSN 1758-678X, 1758-6798. doi: 10.1038/s41558-018-0222-x. URL <https://www.nature.com/articles/s41558-018-0222-x>.
- [161] Sjoukje Y. Philip, Sarah F. Kew, Geert Jan van Oldenborgh, Faron S. Anslow, Sonia I. Seneviratne, Robert Vautard, Dim Coumou, Kristie L. Ebi, Julie Arrighi, Roop Singh, Maarten van Aalst, Carolina Pereira Marghidan, Michael Wehner, Wenchang Yang, Sihan Li, Dominik L. Schumacher, Mathias Hauser, Rémy Bonnet, Linh N. Luu, Flavio Lehner, Nathan Gillett, Jordis S. Tradosky, Gabriel A. Vecchi, Chris Rodell, Roland B. Stull, Rosie Howard, and Friederike E. L. Otto. Rapid attribution analysis of the extraordinary heat wave on the Pacific coast of the US and Canada in June 2021. *Earth System Dynamics*, 13(4):1689–1713, December 2022. ISSN 2190-4979. doi: 10.5194/esd-13-1689-2022. URL <https://esd.copernicus.org/articles/13/1689/2022/>.
- [162] CDC. Underlying Cause of Death, 1999-2020 Request. URL <https://wonder.cdc.gov/ucd-icd10.html>.
- [163] Joycelyne E Ewusie, Charlene Soobiah, Erik Blondal, Joseph Beyene, Lehana Thabane, and Jemila S Hamid. Methods, Applications and Challenges in the Analysis of Interrupted Time Series Data: A Scoping Review. *Journal of Multidisciplinary Healthcare*, Volume 13:411–423, May 2020. ISSN 1178-2390. doi: 10.2147/JMDH.S241085. URL <https://www.dovepress.com/methods-applications-and-challenges-in-the-analysis-of-interrupted-tim-peer-reviewed-art>
- [164] Sean J. Taylor and Benjamin Letham. Forecasting at Scale. *The American Statistician*, 72(1):37–45, January 2018. ISSN 0003-1305, 1537-2731. doi: 10.1080/00031305.2017.1380080. URL <https://www.tandfonline.com/doi/full/10.1080/00031305.2017.1380080>.

- [165] Tianqi Chen and Carlos Guestrin. XGBoost: A Scalable Tree Boosting System. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 785–794, San Francisco California USA, August 2016. ACM. ISBN 978-1-4503-4232-2. doi: 10.1145/2939672.2939785. URL <https://dl.acm.org/doi/10.1145/2939672.2939785>.
- [166] S. N. Lahiri. Theoretical comparisons of block bootstrap methods. *The Annals of Statistics*, 27(1), March 1999. ISSN 0090-5364. doi: 10.1214/aos/1018031117. URL <https://projecteuclid.org/journals/annals-of-statistics/volume-27/issue-1/Theoretical-comparisons-of-block-bootstrap-methods/10.1214/aos/1018031117.full>.
- [167] Puget Sound Energy. Public safety power shutoff, 2025. URL <https://www.pse.com/en/pages/Wildfire-preparedness/Public-Safety-Power-Shutoff>.
- [168] Rupert Way, Matthew C. Ives, Penny Mealy, and J. Doyne Farmer. Empirically grounded technology forecasts and the energy transition. *Joule*, 6(9):2057–2082, September 2022. ISSN 25424351. doi: 10.1016/j.joule.2022.08.009. URL <https://linkinghub.elsevier.com/retrieve/pii/S254243512200410X>.
- [169] Soroush Vahedi, Junbo Zhao, Brian Pierre, Fangni Lei, Emmanouil Anagnostou, Kang He, Charles Jones, and Bin Wang. Wildfire and power grid nexus in a changing climate. *Nature Reviews Electrical Engineering*, 2(4):225–243, April 2025. ISSN 2948-1201. doi: 10.1038/s44287-025-00150-0. URL <https://www.nature.com/articles/s44287-025-00150-0>.
- [170] Zehua Zhao, Jiajia Yang, Fushuan Wen, Julio Romero Agüero, Yang Du, and Mohan V. Jacob. Towards resilient power systems: A review of wildfire mitigation strategies. *Smart Power & Energy Security*, 1(4):175–185, December 2025. ISSN 29498414. doi: 10.1016/j.spes.2025.11.001. URL <https://linkinghub.elsevier.com/retrieve/pii/S2949841425000238>.
- [171] Roman Hoffmann, Anna Dimitrova, Raya Muttarak, Jesus Crespo Cuaresma, and Jonas Peisker. A meta-analysis of country-level studies on environmental change and migration. *Nature Climate Change*, 10(10):904–912, October 2020. ISSN 1758-678X,

- 1758-6798. doi: 10.1038/s41558-020-0898-6. URL <https://www.nature.com/articles/s41558-020-0898-6>.
- [172] David J. Kaczan and Jennifer Orgill-Meyer. The impact of climate change on migration: a synthesis of recent empirical insights. *Climatic Change*, 158(3-4):281–300, February 2020. ISSN 0165-0009, 1573-1480. doi: 10.1007/s10584-019-02560-0. URL <http://link.springer.com/10.1007/s10584-019-02560-0>.
- [173] Kathryn McConnell, Elizabeth Fussell, Jack DeWaard, Stephan Whitaker, Katherine J. Curtis, Lise St. Denis, Jennifer Balch, and Kobie Price. Rare and highly destructive wildfires drive human migration in the U.S. *Nature Communications*, 15(1):6631, August 2024. ISSN 2041-1723. doi: 10.1038/s41467-024-50630-4. URL <https://www.nature.com/articles/s41467-024-50630-4>.
- [174] Lloyd Dixon, Flavia Tsang, and Gary Fitts. The Impact of Changing Wildfire Risks on California’s Residential Insurance Market. *California’s Fourth Climate Change Assessment*, September 2018. URL https://www.rand.org/pubs/external_publications/EP67670.html.
- [175] Katelyn O’Dell, Bonne Ford, Jesse Burkhardt, Sheryl Magzamen, Susan C Anenberg, Jude Bayham, Emily V Fischer, and Jeffrey R Pierce. Outside in: the relationship between indoor and outdoor particulate air quality during wildfire smoke events in western US cities. *Environmental Research: Health*, 1(1):015003, March 2023. ISSN 2752-5309. doi: 10.1088/2752-5309/ac7d69. URL <https://iopscience.iop.org/article/10.1088/2752-5309/ac7d69>.
- [176] Yutong Liang, Deep Sengupta, Mark J. Campmier, David M. Lunderberg, Joshua S. Apte, and Allen H. Goldstein. Wildfire smoke impacts on indoor air quality assessed using crowdsourced data in California. *Proceedings of the National Academy of Sciences*, 118(36):e2106478118, September 2021. ISSN 0027-8424, 1091-6490. doi: 10.1073/pnas.2106478118. URL <https://pnas.org/doi/full/10.1073/pnas.2106478118>.
- [177] Claire L. Schollaert, Jihoon Jung, Joseph Wilkins, Ernesto Alvarado, Jill Baumgartner, Julien Brun, Tania Busch Isaksen, Jamie M. Lydersen, Miriam E. Marlier, Julian D. Marshall, Yuta J.

Masuda, Charles Maxwell, Christopher W. Tessum, Kristen N. Wilson, Nicholas H. Wolff, and June T. Spector. Quantifying the smoke-related public health trade-offs of forest management. *Nature Sustainability*, 7(2):130–139, December 2023. ISSN 2398-9629. doi: 10.1038/s41893-023-01253-y. URL <https://www.nature.com/articles/s41893-023-01253-y>.