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Wildfire Smoke Increases Medicaid Expenditures

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Wildfire activity in the western United States has intensified with climate change, but its fiscal impact on public health systems remains poorly quantified. We combine 7,373 wildfire records with over 2.2 billion Medicaid claim lines across 11 western US states (2018–2024) to estimate how wind-transported wildfire smoke affects healthcare spending. Using random variation in wind direction and speed, we construct a ZIP-code-level exposure index that enables a quasi-experimental design. A 1 $\mu g/m^3$ increase in wildfire-smoke-induced $PM_{2.5}$ increases monthly Medicaid spending by 2.5%, driven primarily by higher spending per patient rather than more patients receiving care. Applying a projected 25% expansion of fire-prone conditions in temperate regions implies approximately $67 million in additional annual Medicaid spending, or $1.6 billion cumulatively by 2050. These findings reveal a substantial and growing fiscal burden of wildfire smoke on public health insurance systems.

Anthropogenic climate change has substantially altered the frequency, extent, and intensity of wildfire activity. Warming temperatures and decreasing atmospheric humidity have increased fuel aridity and fire weather severity with human-caused climate change accounting for roughly 55% of the increase in fuel aridity across western US forests and nearly doubling the forested area burned (Abatzoglou and Williams 2016). These trends are not confined to North America: global analyses indicate that declining relative humidity and rising temperatures drove significant increases in fire weather indices across roughly a quarter to nearly half of the world's burnable land area between 1979 and 2020 (Jain, et al. 2022). Climate projections suggest this expansion will only continue, with the global area subject to frequent fire-prone conditions expected to grow by the end of the century, driven especially by lengthening fire seasons in boreal and temperate zones (Senande-Rivera et al. 2022). Beyond acreage burned and structural damage, the downwind effects of wildfire smoke are a growing and climate-sensitive public health issue that results in

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worsening health outcomes, and as we assess in this paper, a growing burden on public health insurance programs like Medicaid.

Medicaid is a public insurance program jointly run by Federal and state governments in the United States that funds free or low-cost health coverage to more than 80 million individuals with limited financial resources, approximately 32 percent of the population and nearly two in five children (MACPAC, 2024). Coverage includes children, pregnant people, adults, seniors, and people with disabilities. Because Medicaid disproportionately serves low-income and medically vulnerable populations, the program is particularly exposed to the fiscal consequences of increased wildfire smoke exposure. Estimating the effect of wildfire exposure on Medicaid spending therefore informs not only its health consequences, but also the fiscal resilience of a major public insurance program under increasing wildfire activity due to climate change.

A broad synthesis of the epidemiological literature confirms consistent associations between wildfire smoke exposure and both all-cause mortality and respiratory hospitalizations (Gould et al. 2024). Because much of this exposure shaped by unequal capacity for self-protection, behavioral responses to smoke events also vary by income, suggesting that the downstream burden on public healthcare systems, including Medicaid, may be unevenly distributed across populations (Burke et al. 2021).

Here, we develop a ZIP Code specific measure of wind-carried wildfire smoke exposure and link this to expenses documented in the Medicaid system for residents within the ZIP Code. The index of wind-transported wildfire smoke exposure leverages random changes in wind direction such that the measure is large when large fires burn near the ZIP Code and the wind at those fires blow toward it, and near zero when the same fires' smoke is carried elsewhere. By connecting with Medicaid data, this study has a uniquely large population sample with which to document the effect of wildfire smoke on health outcomes and healthcare utilization, and the random variation in wind direction and speed allows us a quasi-experimental framework to determine how wildfire smoke affects healthcare demand. In our instrumental variables regression model, we examine total Medicaid spending, total patients, patients per 1,000 residents, and payment per patient as outcome measures. We also explore heterogeneity by expense category and whether these effects vary across communities with high shares of Black and Hispanic residents, young children, and residents living in poverty.

Prior work has found that the health consequences of smoke exposure span multiple organ systems and life stages. Meta-analytic evidence links short-term exposure to landscape fire smoke particulate matter with elevated rates of asthma hospitalizations and emergency department visits, with older adults and women particularly susceptible (Borchers Arriagada et al. 2019). Wildfire smoke exposure has also been associated with a 70% increase in out-of-hospital cardiac arrest risk, with populations of lower socioeconomic status bearing disproportionate risk (Jones et al. 2020). Exposure during pregnancy has been linked to adverse birth outcomes, including increased risk of

preterm birth (Heft-Neal et al. 2022) and modest reductions in birth weight following in utero exposure (Holstius et al. 2012). Beyond acute physical health effects, wildfire exposure has been tied to elevated rates of PTSD, depression, and anxiety that can persist for years after an event (To et al. 2021), and a broader systematic review identified associations between long-term wildfire exposure and outcomes including cardiovascular and COVID-19 mortality, reduced lung function, and impaired child growth (Gao et al. 2023). Notably, wildfire smoke exposure has also been shown to amplify COVID-19 case and death rates in affected US counties, suggesting interactive effects (Zhou et al. 2021). Recent work has found that some adaptation behavior may be taking place in the face of largescale fires. Gould, et al. 2024 finds that emergency department visits decline on the worst air quality days. The mechanism behind this is that people stay indoors and are not partaking in usual activity that may otherwise result in needed care.

Our study makes two key contributions. First, we use highly granular Medicaid data which is constructed from the healthcare needs of over 80 million individuals. Because Medicaid covers nearly a third of the US population, our sample captures a scale and breadth of coverage among low-income and medically vulnerable groups that is unmatched by prior wildfire-health studies. Second, this work carries direct implications for healthcare utilization and system costs in an era of climate change and increasing wildfire smoke.

The Wildfire West

We use the Western census region in the United States to measure the effect of wildfire smoke on Medicaid utilization. Figure 1 shows the geographic basis for studying the West. Counting every ignition, the West holds 38.9 percent of national fires against 31.8 percent in the South, but its share rises monotonically with fire size to 65.9 percent at ≥ 1,000 acres, 79.3 percent at ≥ 5,000 acres and 94.8 percent of megafires. Transported smoke is generated by large fires, and large fires are overwhelmingly western. The bottom-panel of Figure 1 shows how both wildfire presence and Medicaid expenses vary geographically.

Fire incident records come from the National Interagency Fire Center's InFORM Fire Occurrence Data Records, which consolidate federal agencies' authoritative incident reports—including discovery date, containment date, acreage, and location (NIFC 2026). We obtained 532,287 wildfire incidents for 2018–2024 from NIFC's public feature service (July 2026 vintage). Because InFORM's coverage is most complete from 2020 onward, we backfilled 2018–2020 incidents using the Fire Program Analysis Fire-Occurrence Database (Short 2022), removing duplicate records matched on name, discovery date, and location. The resulting merged catalog contains 674,466 incidents.

Medicaid spending data come from HHS's newly released Medicaid Provider Spending by HCPCS file (U.S. Department of Health and Human Services 2026). Each of the file's original 238 million rows represents a billing-provider–servicing-provider–procedure-code–month combination and reports total paid dollars, claim lines, and distinct beneficiaries. The data span January 2018–December 2024, cover Medicaid fee-for-service, managed care, and CHIP, and total approximately $1.03 trillion in payments.[3] Providers were geolocated to their practice ZIP code giving the paper's geographic unit of analysis, the billing provider's 2020 ZIP Code Tabulation Area. Other data sources are discussed in the online methodology appendix.

Wildfire Smoke Exposure

A central challenge in studying the health effects of wildfire smoke is that areas near frequent fire activity often differ systematically from other areas, and these differences could independently affect Medicaid enrollment in the first place. Simply comparing Medicaid spending in high-fire versus low-fire ZIP Codes therefore risks confusing the effect of smoke with other features that make fire-prone places distinctive. A common solution to this problem is to find a source of variation (the instrument) that shifts exposure to the phenomenon of interest without itself being related to the confounding factors. Wind direction is a natural candidate for smoke exposure: whether a fire's smoke reaches a given community on a given day depends on which way the wind happens to be blowing. Because short-run wind direction is essentially unrelated to a ZIP Code's economic or demographic characteristics, it isolates variation in smoke exposure that is plausibly independent.

Wind direction has a well-established track record as a source of identifying variation in the economics of air pollution, including studies instrumenting county-level $PM_{2.5}$ with daily wind direction (Deryugina et al. 2019), weighting downwind highway exposure by wind alignment (Anderson 2020), and comparing downwind and upwind communities near urban highways (Herrnstadt et al. 2021). Fire-specific applications of similar logic include agricultural burning in Brazil (Rangel and Vogl 2019), straw burning in China (Graff Zivin et al. 2020; He et al. 2020), biomass fires and birth outcomes globally (Pullabhotla et al. 2023), and Santa Ana wind-driven smoke exposure in Southern California (Aguilera et al. 2021). Our index combines three previously used elements—fire size, cosine-weighted wind alignment, and distance decay—into a single continuous measure, distinct from approaches that instead observe realized smoke plumes directly via satellite which could suffer from measurement error (Miller, Molitor and Zou 2024; Borgschulte, Molitor and Zou 2024). Two placebo indices, substituting upwind and crosswind

[3] The largest spending categories are home- and community-based services (28%), evaluation-and-management visits (16%), and behavioral health/substance-use services (14%).

weighting using the same fires and distances, yield precise null effects, supporting our identifying assumption.

Figure 2 shows how the wind-driven exposure index is built using the event that delivered the greatest population-weighted exposure in our data as an example: the LNU Lightning Complex, which burned 363,220 acres in the Northern California Coast Ranges in August 2020. The figure shows each nearby ZIP Code's share of the fire's total contribution to the index, the wind vector the index uses and the sharp boundary beyond which cosine-weighted wind alignment turns negative, and exposure drops to exactly zero. In total, this one fire-month generated positive exposure for 999 ZIP Codes containing 17.1 million people, with the most exposed community only 18 km from the fire.

Worse Health Outcomes and More Spending

We find that there is a 2.52% increase in monthly Medicaid spending for a 1 $\mu g/m^3$ increase in downwind wildfire-smoke-induced $PM_{2.5}$ exposure. To put this in context, moving from no downwind wildfire exposure to the average level observed in our sample increases wildfire-smoke-induced $PM_{2.5}$ by approximately 0.41 $\mu g/m^3$ and raises monthly Medicaid spending by about 1.03%, roughly $8,100 for the average ZIP Code-month; statistically significant at the 5% level.[4] Applying the estimated 1.03% increase to the near $177.4 billion in Medicaid spending represented in our estimation sample implies an aggregate increase of about $1.83 billion in Medicaid expenditures associated with moving from no downwind wildfire exposure to the average level observed in the sample.

To illustrate the magnitude of these costs for a single major wildfire, consider the Dixie Fire, one of the largest fires in our sample. The Dixie Fire increased monthly Medicaid spending by an estimated 0.37% across affected ZIP Codes, corresponding to approximately $1,862 per affected ZIP Code-month. Across 2,554 affected ZIP Code-months from July through October 2021, this amounted to approximately $4.8 million in additional Medicaid spending through increases in $PM_{2.5}$ associated with wildfire smoke.[5]

[4] Note, we refer to the instrumental variables (two-stage least squares) estimates exclusively within the body of the text because this is our preferred model specification, but we also present the reduced-form estimates side-by-side with the IV estimates in figures for completeness. The reduced form estimates the effect of the wind-driven downwind exposure index directly on Medicaid spending, whereas the IV specification uses this wind-driven variation to isolate changes in ambient $PM_{2.5}$. Because the reduced-form and IV coefficients are expressed in different units, their magnitudes are not directly comparable.

[5] To scale the Dixie Fire, we estimate that an additional 100,000 acres of nearby fire activity increases the downwind exposure index by 0.223 units. Given Dixie's 963,309 acres, this implies a 2.148-unit increase in exposure, which raises $PM_{2.5}$ by 0.146 $\mu g/m^3$ and Medicaid spending by approximately 0.37%. Applying this effect to the roughly

Figure 3 shows individual coefficient estimates from the instrumental variables regressions shown in Appendix Tables A1 and A2 from the online methods appendix. Here, we break down the total effect of a unit increase in wildfire-caused $PM_{2.5}$ exposure (2.52%) into the extensive and intensive margins that drive the change in total spending by ZIP Code. The extensive margin refers to the number of people receiving care following a wildfire event. The intensive margin refers to the severity or intensity of care needed per person. We find that the main determinant of increased Medicaid usage after exposure to a wildfire is at the intensive margin. Expenses per person increase by 3.45% for each unit increase in wildfire exposure, but the estimate for total number of persons receiving care falls by 0.93% (though statistically zero). The result that the total number of people seeking care may decline following a wildfire has precedent in the literature (Gould, et al. 2024). This shows that wildfire smoke exposure is driving significant changes in the intensity of care needed.

Table 1 shows that the spending response extends across multiple parts of the healthcare system. For a shift from no downwind wildfire exposure to the average level observed in our sample, estimated spending rises by 1.5% for office visits, laboratory services and surgery; 1.7% for imaging and durable equipment; 1.3% for behavioral health, transport and rehabilitation; and 0.9% for the broad category covering long-term and home care, acute care, dental services, drugs, respiratory care and other services. The office visits, laboratory services and surgery estimate is statistically significant at the 5% level, whereas the remaining estimates are less precise. Combining each category's share of Medicaid payments with its estimated response suggests that the broad final category accounts for nearly half of the aggregate dollar increase, indicating that wildfire smoke creates a diffuse fiscal burden across the healthcare system rather than operating through a single type of care.

Finally, we ask whether the fiscal burden of wildfire smoke falls evenly across communities. We re-estimate the model interacting instrumented $PM_{2.5}$ with an indicator for ZIP Codes holding the top population quartile of a given demographic characteristic and plot the effect for each group in Figure 4. Wildfire smoke raises Medicaid spending in every group we examine.[6] The response is largest in ZIP Codes with the highest shares of children under age three (3.75% per $\mu g/m^3$), Hispanic residents (3.55% per $\mu g/m^3$), Black residents (2.95% per $\mu g/m^3$), and Zip Codes with high poverty rate (2.68% per $\mu g/m^3$). These patterns are consistent with a broader literature documenting heightened vulnerability to wildfire smoke among children and larger pollution-related health effects among Black and socioeconomically disadvantaged populations (Jbaily et al., 2022; Mikati et al., 2018; Tessum et al., 2019).

$1.30 billion in Medicaid spending across 2,554 affected ZIP Code-months yields approximately $4.8 million in additional Medicaid expenditures attributable to smoke-related $PM_{2.5}$.

[6] The marginal effects for all four groups are statistically significant at the 5% level.

Alternative Drivers of Change

There are reasonable counterarguments to our finding that wildfire smoke increases Medicaid usage. For one, the discrepancy could instead be driven by the effect of heat on Medicaid usage as shown in Roach and Noghanibehambari (2026), and thus our result may not be related to wildfire smoke because hot days and smoke days tend to align. Similarly, increased expenses could be driven by market concentration effects and the availability, or lack thereof, of providers in rural areas where both Medicaid enrollment and wildfire smoke may be more likely. Another confounding issue could be the severity of COVID-19 in a ZIP Code, as our sample runs from 2018–2024 and includes several years in which COVID-19 spread was high. Figure 5 explores these possibilities. The first estimate is based on a parsimonious model that excludes the temperature, precipitation, and wind controls included in our main specification, and subsequent estimates add back these weather controls or introduce additional controls for provider availability, housing prices, COVID-19 severity, and ZIP Code-specific annual shocks. Here, we see that neither excluding the main weather controls nor adding these additional controls materially changes the estimated coefficient: the effect remains close to the main estimate of a 2.52% increase in monthly Medicaid spending for a 1 $\mu g/m^3$ increase in wildfire-smoke-induced $PM_{2.5}$, and all robustness estimates are statistically significant at the 95% level or better. In fact, several specifications show that wildfire smoke may have a slightly larger effect than what was found in our main model.

Finally, the online methods appendix also shows that our results are robust to removing overly influential observations both by geography and by time, and when varying the minimum fire size included in the exposure index. Appendix Figure A-4 also reveals a suggestive fire-size gradient. The point estimate rises from 2.52% per $\mu g/m^3$ at the 100-acre baseline to approximately 5–6% once the exposure index is restricted to fires of at least 400 acres or greater and remains elevated as the cutoff increases to 1,000 acres. This pattern suggests that the Medicaid spending response is substantially greater when smoke exposure is driven by larger fires and that the baseline estimate is conservative.

Discussion

As climate change leads to drier and hotter conditions, wildfires across the western United States have increased in both their frequency and severity. Smoke from these wildfires pose both immediate and longer-term health concerns, and recent work in this field is only beginning to quantify the downwind costs of heightened fire activity (Gould et al. 2024).

In this work, we analyze realized healthcare demand in response to wildfire smoke exposure using highly granular Medicaid data. Because Medicaid covers nearly a third of the US

population, our sample captures a scale and breadth of coverage among low-income and medically vulnerable groups that is unmatched by prior wildfire-health studies. Using exogenous variation in wind direction and speed, we are able to approximate experimental conditions in smoke exposure by zip code yielding credible estimates of how wildfire smoke harms health outcomes. We find that wildfire smoke is associated with a 2.52% increase in Medicaid expenses and this is driven by an increase in the amount spent per patient, not an increase in the number of patients needing care. We also find larger pollution-related health effects in ZIP codes with large Black, Hispanic, and socioeconomically disadvantaged populations, as well as those with more children.

These added costs are likely to become increasingly important as climate change expands the conditions conducive to wildfire activity. As an illustrative extrapolation, applying the Senande-Rivera, et al. (2022) projected 25% expansion of fire-prone conditions in temperate regions to our estimated fiscal burden implies approximately $67 million in additional Medicaid spending annually, or about $1.6 billion in cumulative additional spending by 2050.[7]

[7] These projections assume that wildfire-related Medicaid costs increase proportionally with fire-prone conditions, hold Medicaid enrollment fixed at current levels, and are expressed in today's dollars.

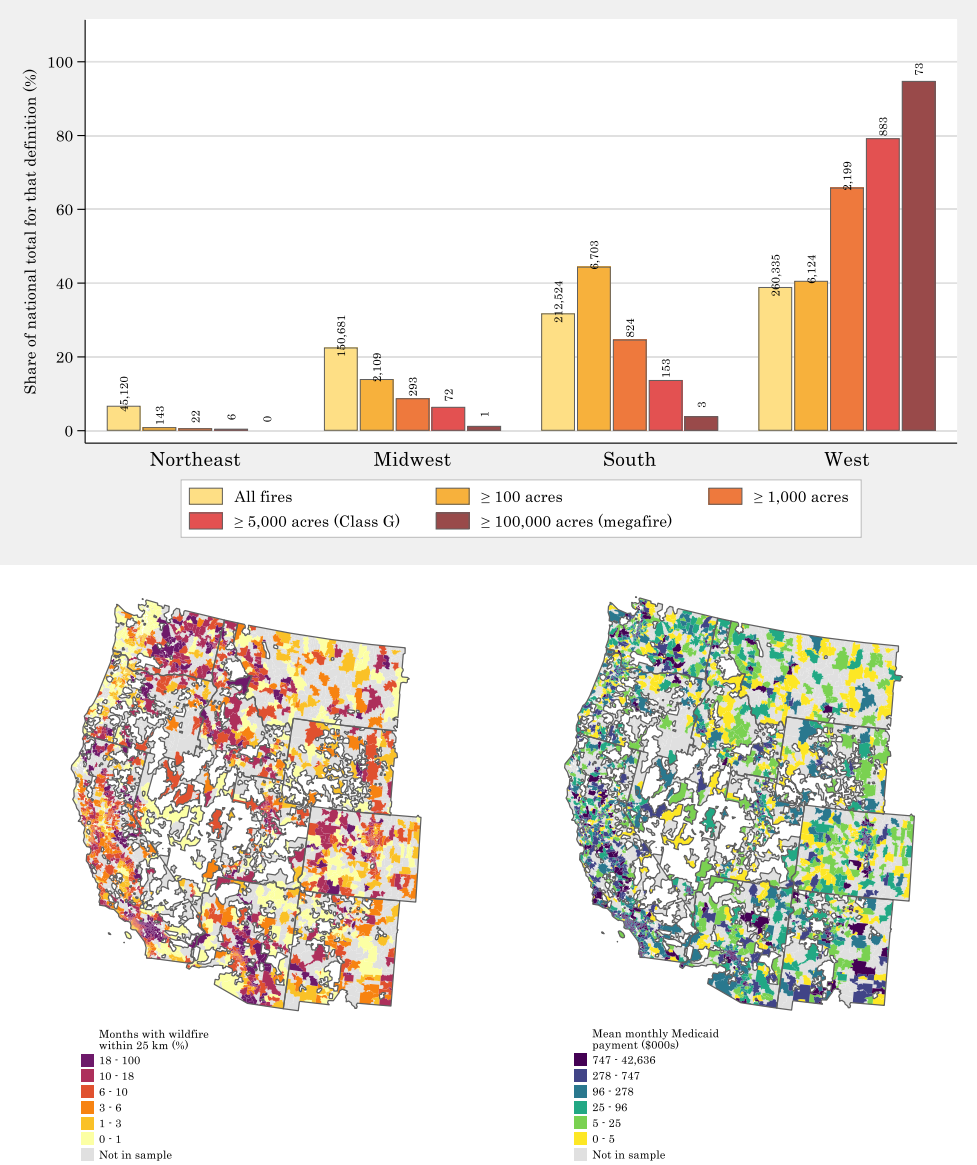

Figure 1. Regional Distribution of Wildfires under Five Size Definitions, Spending by ZIP Code

Top panel notes: Each bar is the share of the NATIONAL (CONUS) total for that size definition held by that Census region, so the four bars of one color sum to 100; the underlying count is printed above each bar. Alaska, Hawaii and the territories are excluded here exactly as they are from the estimation sample, because gridMET wind does not cover them. The ≥ 5,000-acre cut is National Wildfire Coordinating Group Size Class G, the largest official federal size class; ≥ 100,000 acres is the conventional megafire threshold.

Bottom panel notes: The left panel shades by the share of sample months with a wildfire within 25 km (custom breaks); right panel by mean monthly Medicaid payment in $000s (sextiles). Colored ZIP Codes are in the estimation sample; light grey ZIP Codes are in the eleven states but have no Medicaid billing provider; white areas are not covered by any ZCTA, chiefly unpopulated federal land. Alaska and Hawaii are omitted

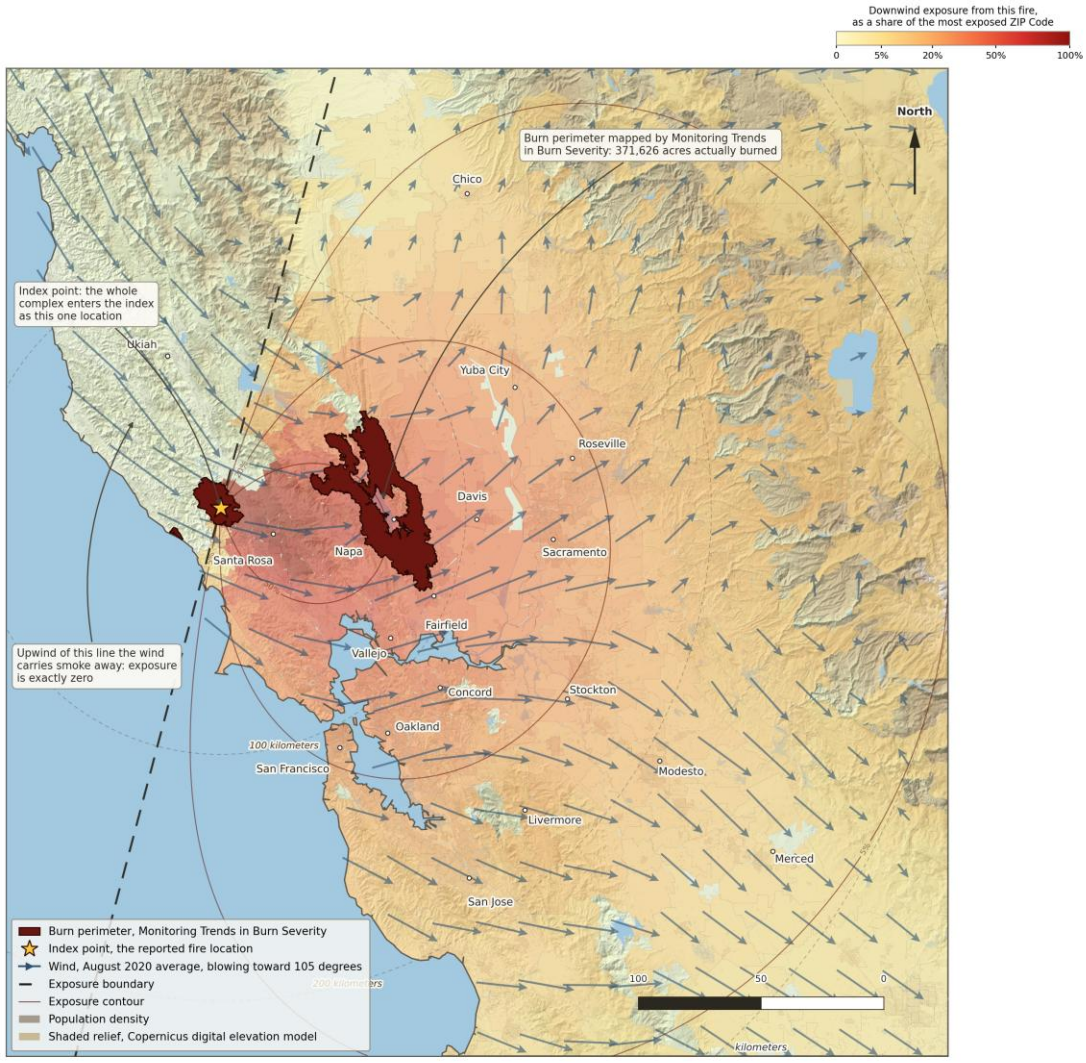

Figure 2. How the Downwind Exposure Measure Is Built: One Wildfire

Notes. A worked example of the treatment IV on the fire that delivered the most exposure to people in the whole sample. Every western fire-month of at least 50,000 acres was ranked by population times its own term in the exposure index, and the LNU Lightning Complex of August 2020 ranks first: 363,220 acres in the Northern California Coast Ranges. Shading gives each ZIP Code that fire's contribution to the index, as a share of the most exposed ZIP Code; the dashed line is the boundary beyond which cos θ turns negative and exposure is exactly zero; dashed circles mark distance from the fire and the contours mark the continuous field behind the ZIP Code averages. Arrows are the gridMET wind, averaged over August as VECTORS rather than as bearings, blowing toward 105° at 4.9 m/s. Note the gap between the burn perimeter, which is mapped, and the gold star, which is the single reported point the index actually uses: the complex is represented at its western Wallbridge component, about 67 km west of the much larger Hennessey mass, so the exposure lobe is displaced west of where most of the burning happened. In total this one fire gave positive exposure to 999 ZIP Codes holding 17.1 million people, the most exposed being 18 km away.

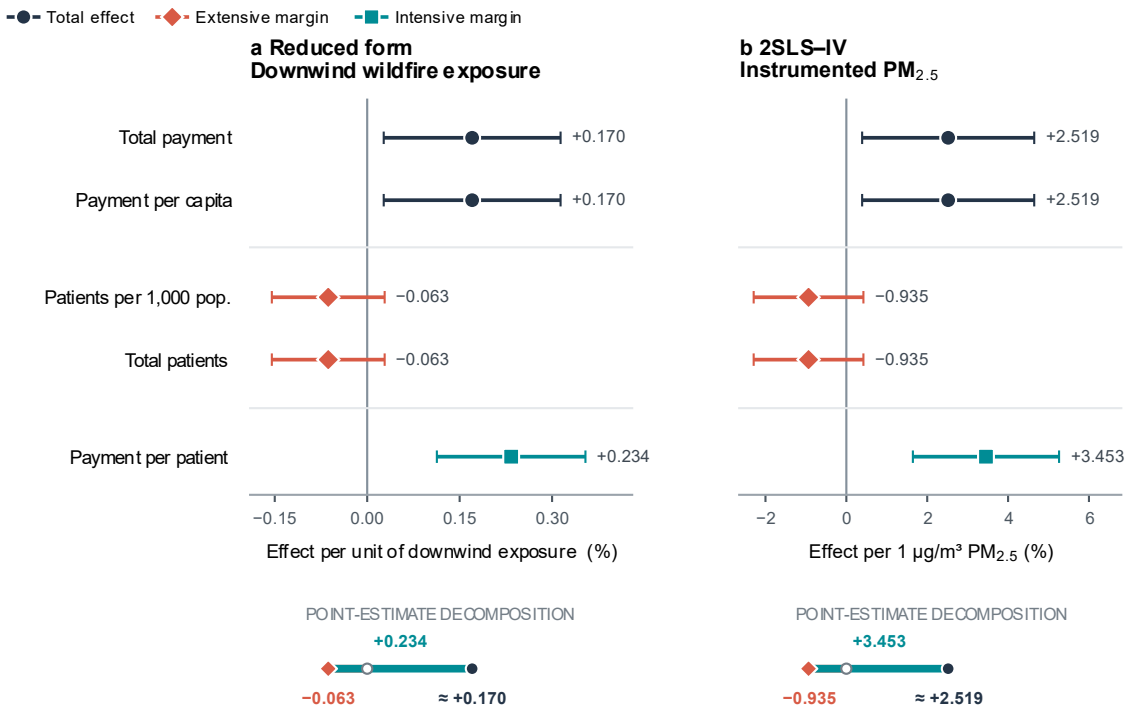

Figure 3. Medicaid Spending Response, by Utilization Margin

Points show coefficient estimates and horizontal lines show 95 percent confidence intervals. Panel A reports reduced-form estimates of each outcome on the downwind wildfire index, while Panel B reports 2SLS estimates that instrument ambient PM2.5 with this index. Outcomes are measured as (100 X log), so coefficients represent approximate percentage changes. Total patients and patients per 1,000 residents capture the extensive margin, while payment per patient captures the intensive margin.

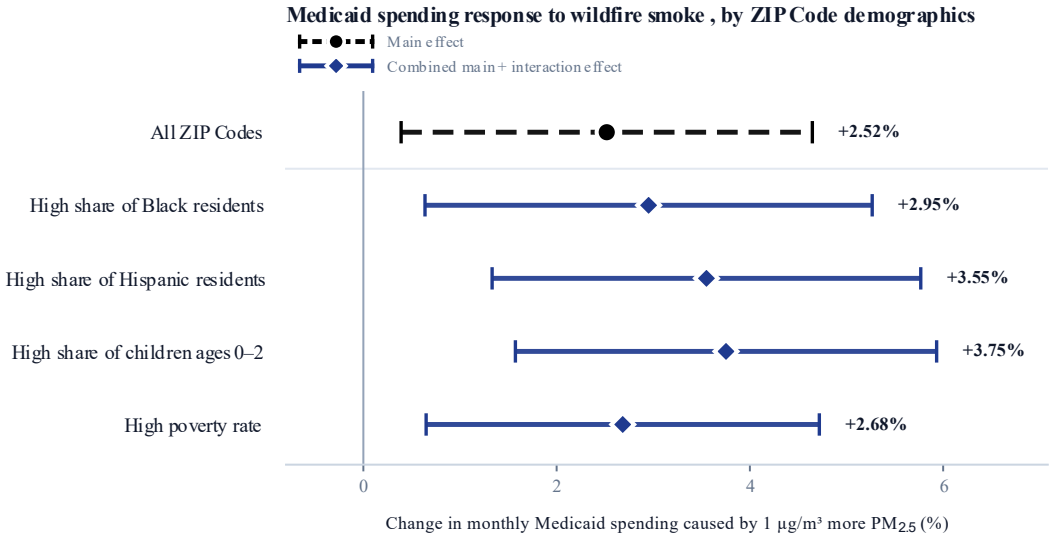

Figure 4. Heterogeneity in Medicaid Spending Responses to Wildfire Smoke by ZIP Code Demographics

Notes. Points show two-stage least squares estimates of the effect of wildfire-smoke-induced fine particulate matter ($PM_{2.5}$) on monthly Medicaid spending; horizontal lines show 95% confidence intervals. Monthly Medicaid spending is measured as 100 × log, so coefficients represent approximate percentage changes associated with a 1 µg/m³ increase in $PM_{2.5}$. The black circle reports the estimate for all ZIP Codes, while blue diamonds report the combined effect for ZIP Codes in the top quartile of the share of Black residents, share of Hispanic residents, share of children ages 0–2, and poverty rate. $PM_{2.5}$ is instrumented using the downwind wildfire exposure index.

Table 1. Medicaid Payments by Category of Service

Category of service	(1) Share of payments	(2) IV Estimate	(3) Change at average exposure level (0.41 μg/m³)	(4) Observations
Office visits, laboratory and surgery	12.5	3.549** (1.716)	1.46%	188,297
Imaging and durable equipment	5.1	4.101* (2.360)	1.68%	125,834
Behavioral health, transport and rehabilitation	25.0	3.046 (1.964)	1.25%	173,943
Long-term and home care, acute care, dental, drugs, respiratory and other	57.4	2.161* (1.199)	0.89%	212,232
All services	100.0	2.519** (1.086)	1.03%	226,301

The outcome is the same as in Appendix Table A1, Panel C, column (2), 100 × log(Medicaid payment); only the set of HCPCS codes it is summed over changes across rows. Each row's payment is the estimation sample's total payment apportioned by that group's share of the ZIP-month's provider-HCPCS billing, so the final row reproduces Appendix Table A1, Panel C, column (2). The four groups are mutually exclusive and exhaustive and their shares sum to 100. Column 1 is the group's share of Medicaid payments; column 2 is the two-stage least squares estimate on ambient PM2.5 (μg/m³) instrumented by X; column 3 translates the coefficient into the effect at the average downwind exposure level; column 4 number of ZIP-months, which varies because a ZIP-month enters a row only if it has positive payment in that group.

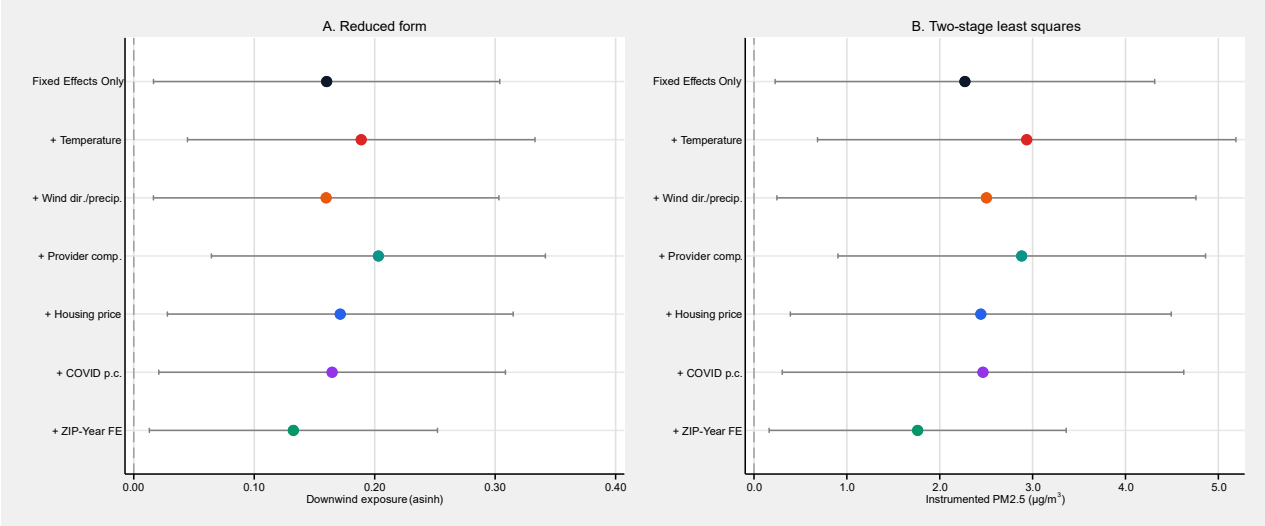

Figure 5. Robustness of the Medicaid Spending Response across Specifications

Notes. Coefficients with 95 percent confidence intervals from seven specifications; the dashed grey line marks the baseline. BASELINE is pared back model with fire-ring controls with ZIP Code × calendar-month and Year–Month fixed effects. Each later row adds ONE block to that baseline: TEMPERATURE, days of the month in each of 16 maximum-temperature bins (modal bin omitted); WIND DIR./PRECIP., gridMET monthly wind direction in degrees and precipitation; PROVIDER COMP., asinh distinct provider-HCPCS billing cells per 1,000 residents, proxying local provider supply; HOUSING PRICE, Zillow Home Value Index quartile dummies plus a missing dummy; COVID P.C., county COVID-19 cases per capita in quartile dummies plus a missing dummy (zero before 2020); ZIP-YEAR FE, adding ZIP Code × year fixed effects. Quartile-plus-missing encoding keeps the full sample where a series is unavailable. Panel A is the reduced form, Panel B 2SLS instrumented PM2.5. N ranges from 225,775 to 226,301

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Online Methods Section

Anecdotal evidence that wildfire smoke increases Medicaid expenditures, and thus, healthcare demand is shown in Appendix Figure A-1. The red line is a population-weighted linear fit, but this is a raw cross-section with no fixed effects or controls, so it is descriptive only and is confounded by the fact that fire-prone ZIP Codes are typically rural and smaller. The instrumental variables model controls for such differences with ZIP Code fixed effects in addition to other important factors described below.

We construct a monthly, ZIP Code-level measure of wind-transported wildfire smoke exposure. For each ZIP Code and month, every wildfire of at least 100 acres within 500 km contributes to the exposure index according to:

$$acres_f \times \max\left(cos\theta_{fz}, 0\right) \times \exp(-\frac{d_{fz}}{100})$$

where $acres_f$ is the size of fire f, θ_{fz} is the angle between the direction in which the wind is blowing at the fire and the direction from the fire to ZIP Code z, and d_{fz} is the distance between the fire and the ZIP Code in kilometers. Thus, larger and closer fires contribute more to the index, but only when the wind is blowing toward the ZIP Code. Of the incidents in the merged wildfire catalog, 7,373 unique fires satisfy the criteria for inclusion in the exposure index. Because a fire can contribute exposure in more than one calendar month, these fires generate 22,270 qualifying fire-months in the estimation sample.

We sum these contributions across all qualifying fires and apply an inverse hyperbolic sine transformation to accommodate ZIP Code-months with zero exposure. We also control for total fire activity in five distance bands: 0–25, 25–50, 50–100, 100–250, and 250–500 km. These controls absorb variation associated with simply being near wildfire activity, so identification comes from whether prevailing winds carry smoke toward a ZIP Code rather than from fire proximity alone. Because the exposure measure is constructed from fire location, fire size, wind direction, and distance rather than observed or modeled smoke concentrations, it also reduces concerns about measurement error in realized smoke exposure.

We use the downwind exposure index as an instrument for ambient $PM_{2.5}$ in a standard two-stage least squares framework. The first stage is:

$$PM_{zt} = \pi X_{zt} + W'_{zt}\Gamma + \mu_{z,m(t)} + \lambda_t + \nu_{zt}$$

where PM_{zt} is ambient $PM_{2.5}$ in ZIP Code z and month t, X_{zt} is the downwind wildfire exposure index, and W_{zt} contains the weather and fire-activity controls. The term μ denotes ZIP Code × calendar-month fixed effects, which absorb persistent seasonal patterns specific to each ZIP Code, while λ denotes year-month fixed effects, which absorb shocks common to all ZIP Codes in a given month.

The second stage uses the component of $PM_{2.5}$ predicted by wind-driven wildfire exposure to estimate its effect on Medicaid outcomes:

$$Y_{zt} = \beta \widehat{PM}_{zt} + W'_{zt}\Theta + \mu_{z,m(t)} + \lambda_t + \varepsilon_{zt}$$

The outcome Y_{zt} is measured as $100 \times log(Medicaid\ outcome)$. Accordingly, β gives the approximate percentage change in the Medicaid outcome associated with a 1 μg/m³ increase in wildfire-smoke-induced $PM_{2.5}$.

Our preferred specification controls for temperature, precipitation, wind speed, and fire activity in the five distance bands and includes ZIP Code × calendar-month and Year-Month fixed effects. Figure 5 shows that the estimated effect is largely unchanged when these weather controls are excluded or when additional controls for provider availability, housing prices, COVID-19 severity, and ZIP Code-specific annual shocks are added.

All regressions are weighted by 2020 ZIP Code population, and standard errors are clustered by ZIP Code × calendar-month. The final estimation sample contains 226,301 ZIP Code-month observations across 11 western states from January 2018 through October 2024.

Data source descriptions:

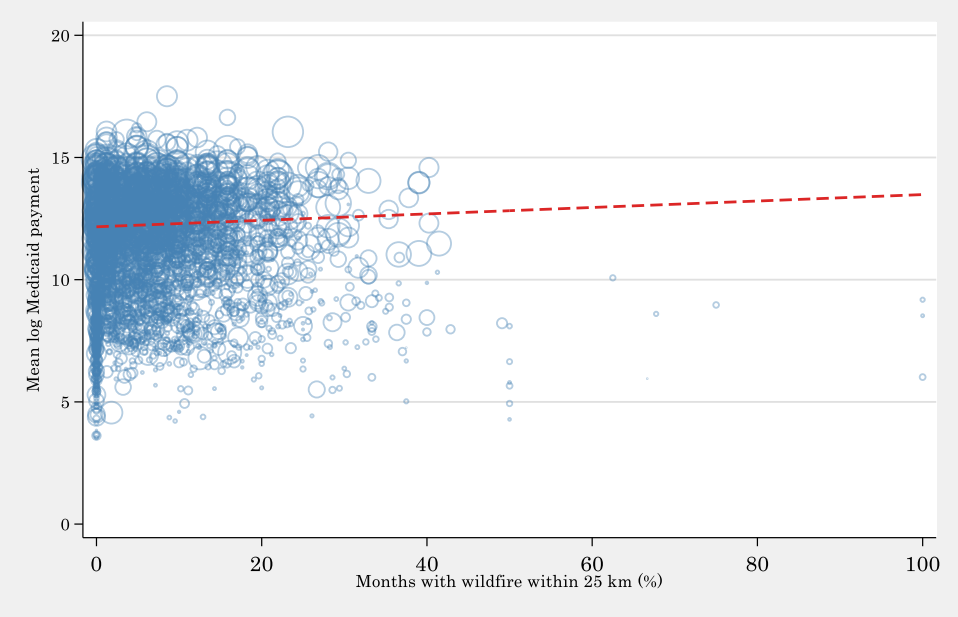
Wildfire: Wildfire records come from the National Interagency Fire Center (NIFC), which brings together official reports from federal agencies on when and where fires occurred, when they were contained, and how many acres they burned (NIFC 2026). We downloaded 532,287 wildfire records covering 2018–2024 in July 2026. Because these records are more complete from 2020 onward, we supplemented the 2018–2020 data using the Fire Program Analysis Fire-Occurrence Database (Short 2022) and removed duplicate fires based on their names, dates, and locations. The combined data contain 674,466 wildfire incidents. Fire size is measured using the acreage reported by the responsible agencies; when acreage is missing, we use satellite maps of burned areas. We also use burned-area maps from Monitoring Trends in Burn Severity as an independent check on reported fire size (Eidenshink et al. 2007).

Medicaid: Medicaid spending data come from the U.S. Department of Health and Human Services Medicaid Provider Spending by Healthcare Common Procedure Coding System file, released in February 2026 and based on the Transformed Medicaid Statistical Information System. The file contains 238 million records covering January 2018 through December 2024, with information on payments, services provided, and the number of Medicaid beneficiaries receiving care. These records summarize more than nine billion individual claim lines, of which 2.27 billion fall within our estimation sample. The data include traditional fee-for-service Medicaid, Medicaid managed care, and the Children's Health Insurance Program, and contain approximately $1.03 trillion in total payments. The largest spending categories are home- and community-based services (28%), evaluation and management visits (16%), and behavioral health and substance-use services (14%). We identify each provider's practice location using the Centers for Medicare & Medicaid Services National Plan and Provider Enumeration System and assign spending to the provider's 2020 ZIP

Code Tabulation Area. The resulting geolocated analysis file retains approximately $534 billion in payments; records that cannot be assigned to a valid ZIP Code Tabulation Area are excluded. Population measures used for weighting and per-person calculations come from the 2020 U.S. Census (U.S. Census Bureau 2023).

Air pollution: We measure ambient fine particulate matter ($PM_{2.5}$) using the SatPM V6.GL.03 dataset (Shen et al. 2024; van Donkelaar et al. 2021). This dataset combines satellite observations, computer models of atmospheric pollution, and readings from ground-based air-quality monitors to provide monthly $PM_{2.5}$ concentrations at a resolution of approximately 1 kilometer. For each ZIP Code, we assign the $PM_{2.5}$ value at its U.S. Census-designated internal point for each month from January 2018 through December 2024. We also compare these measures with readings from U.S. Environmental Protection Agency (EPA) air-quality monitors as an independent check.

Weather: Weather data come from gridMET (Abatzoglou 2013), which provides daily weather information across the contiguous United States at a resolution of approximately 4 kilometers. For each ZIP Code and month, we calculate average wind speed and wind direction and measure daily maximum temperature. We also count the number of days in each month when the maximum temperature reaches at least 80°F, 90°F, and 100°F. The number of days reaching at least 80°F is our main measure for accounting for temperature in the analysis.



Appendix Figure A-1. Wildfire Prevalence and Medicaid Spending across ZIP Codes (Cross-Section)

Notes. One hollow circle per ZIP Code, sized by 2020 population: the share of its sample months with a wildfire within 25 km against its mean log monthly Medicaid payment. Sample: ZIP Code (2020 ZCTA) × month, 11 western states, 2018m1–2024m10 (2024m11–m12 dropped for Medicaid claims runout); ZIP Code = billing provider's ZIP Code. Wildfire prevalence = share of ZIP-months with an InFORM fire of at least 100 acres within 25 km.

Tables of Estimates

Appendix Table A1. Downwind Wildfire Exposure, Ambient PM2.5 and Medicaid Spending

	(1)	(2)
Fixed effects:	*ZIP + month + year*	*ZIP × month + Year-Month*
Panel A. Reduced form – outcome: 100 × log(Medicaid paid)		
Downwind exposure, X	0.143**	0.170**
	(0.057)	(0.073)
R-squared	0.881	0.895
Mean of outcome	1242.2	1242.7
Panel B. First stage – outcome: ambient PM2.5 (μg/m³)		
Downwind exposure, X	0.110***	0.068***
	(0.003)	(0.004)
R-squared	0.437	0.658
Mean of outcome	8.49	8.50
Panel C. 2SLS – outcome: 100 × log(Medicaid paid)		
Ambient PM2.5 (μg/m³),	1.299**	2.519**
	(0.522)	(1.086)
First-stage F (Kleibergen–Paap)	1222	378
Observations (2SLS)	228,038	226,301
ZIP Code FE	✓	
Calendar-month FE	✓	
Year FE	✓	
ZIP Code × calendar-month FE		✓
Year–Month FE		✓
Weather and fire-ring controls	✓	✓
Observations (OLS)	228,038	226,301
ZIP × calendar-month clusters	37,767	36,030

*Notes. The unit of observation is the ZIP Code × month. The sample covers 11 western states (Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, and Wyoming) from January 2018 through October 2024; November and December 2024 are excluded because of incomplete claims. In Panels A and C, the outcome is 100 × log of total monthly Medicaid payments, so coefficients represent approximate percentage changes in Medicaid spending. In Panel B, the outcome is ambient fine particulate matter ($PM_{2.5}$), measured in micrograms per cubic meter (μg/m³). X is the inverse-hyperbolic-sine-transformed downwind wildfire exposure index, constructed from wildfires of at least 100 acres within 500 km and weighted by fire acreage, wind alignment toward the ZIP Code, and distance decay. Panel A reports reduced-form estimates of Medicaid spending on X; Panel B reports the first-stage relationship between X and ambient $PM_{2.5}$; and Panel C reports two-stage least squares estimates in which ambient $PM_{2.5}$ is instrumented by X. Column (1) includes ZIP Code, calendar-month, and year fixed effects; column (2) includes ZIP Code × calendar-month and Year-Month fixed effects. All specifications control for the number of days with maximum temperature at or above 80°F, precipitation, wind speed, and the inverse hyperbolic sine of wildfire acreage in five distance bands (0–25, 25–50, 50–100, 100–250, and 250–500 km). Observations are weighted by 2020 ZIP Code population, and standard errors are clustered by ZIP Code × calendar-month and reported in parentheses. The Kleibergen–Paap statistic reports first-stage instrument strength. *** p<0.01, ** p<0.05, * p<0.10.*

Appendix Table A2. Utilization and Spending Margins: Extensive versus Intensive

		Reduced form		Two-stage least squares		
Outcome (100 × log)	**Margin**	**Coefficient**	**(SE)**	**Coefficient**	**(SE)**	**Observations**
Total payment	*Total*	0.170**	(0.073)	2.519**	(1.086)	226,301
Payment per capita	*Total*	0.170**	(0.073)	2.519**	(1.086)	226,301
Patients per 1,000 pop.	*Extensive*	-0.063	(0.047)	-0.935	(0.692)	226,301
Total patients	*Extensive*	-0.063	(0.047)	-0.935	(0.692)	226,301
Payment per patient	*Intensive*	0.234***	(0.061)	3.453***	(0.922)	226,301
First-stage F (Kleibergen–Paap)				*378*		

*Notes. The unit of observation is the ZIP Code × month. The sample covers 11 western states (Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, and Wyoming) from January 2018 through October 2024; November and December 2024 are excluded because of incomplete claims. Each outcome is measured as 100 × log, so coefficients represent approximate percentage changes. Total payment is monthly Medicaid spending; payment per capita divides monthly spending by 2020 ZIP Code population; patients per 1,000 population measures the number of patients relative to ZIP Code population; total patients is the monthly patient count; and payment per patient divides total monthly payments by the patient count. Total patients and patients per 1,000 population capture the extensive margin, while payment per patient captures the intensive margin. Reduced-form estimates regress each outcome on X, the inverse-hyperbolic-sine-transformed downwind wildfire exposure index constructed from wildfires of at least 100 acres within 500 km and weighted by fire acreage, wind alignment toward the ZIP Code, and distance decay. Two-stage least squares estimates report the effect of ambient fine particulate matter ($PM_{2.5}$), measured in micrograms per cubic meter ($\mu g/m^3$), instrumented by X. All specifications include ZIP Code × calendar-month and Year-Month fixed effects and control for the number of days with maximum temperature at or above 80°F, precipitation, wind speed, and the inverse hyperbolic sine of wildfire acreage in five distance bands (0–25, 25–50, 50–100, 100–250, and 250–500 km). Observations are weighted by 2020 ZIP Code population, and standard errors are clustered by ZIP Code × calendar-month. The Kleibergen–Paap statistic reports first-stage instrument strength. *** p<0.01, ** p<0.05, * p<0.10.*

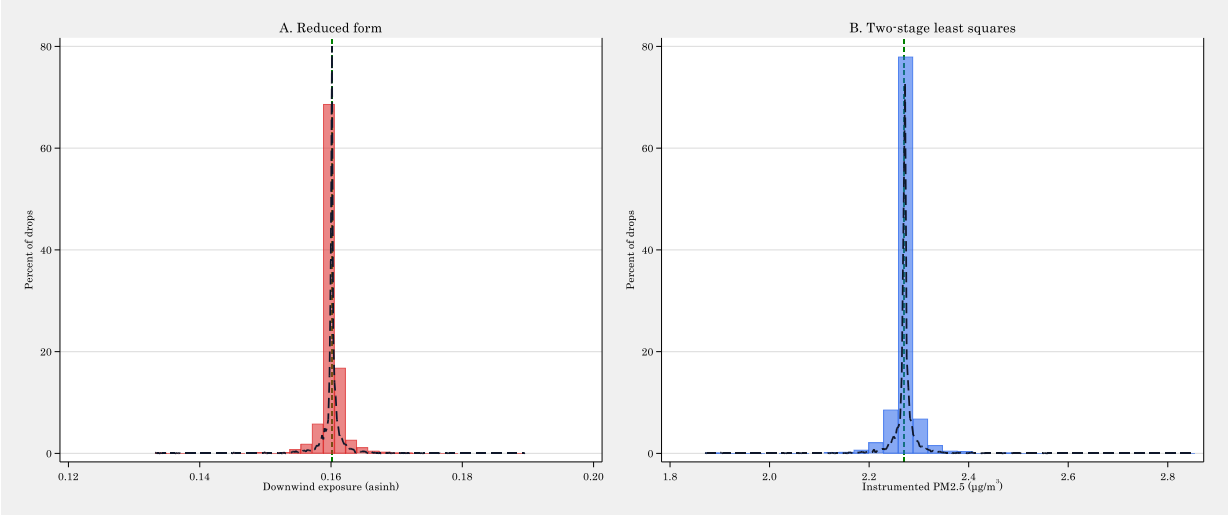
Appendix Table A3. Summary Statistics

	Weighted mean	SD	N
Total Medicaid payment ($ thousand)	784.0	1,453.6	226,301
Medicaid patients	10,149	19,850	226,301
Claim lines (thousand)	15.1	28.1	226,301
Ambient PM2.5 (μg/m³)	8.50	5.49	226,301
Downwind exposure index, (asinh acre-equivalents)	6.03	3.88	226,301
Any downwind exposure (share)	0.82	0.39	226,301
Days with max temperature ≥ 80°F	9.6	11.0	226,301
Precipitation (mm)	1.3	2.1	226,301
Wind speed (m/s)	3.20	0.89	226,301
Fire acres within 0–25 km (thousand)	0.91	12.42	226,301
Fire acres within 25–100 km (thousand)	21.2	73.4	226,301
Fire acres within 100–500 km (thousand)	281.7	439.4	226,301
2020 population (thousand)	40.4	20.0	226,301
Share Black, non-Hispanic (%)	4.5	5.4	226,301
Share Hispanic (%)	31.4	22.4	226,301
Share aged 0–2 (%)	3.21	1.03	226,301
Poverty rate (%)	11.7	9.0	226,301

Notes. Summary statistics are reported for the two-stage least squares estimation sample covering ZIP Code-months in 11 western states (Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, and Wyoming) from January 2018 through October 2024; November and December 2024 are excluded because of incomplete claims. Means are weighted by 2020 ZIP Code population. Total Medicaid payment is monthly Medicaid spending in thousands of dollars; Medicaid patients is the monthly patient count; and claim lines is the monthly number of claim lines in thousands. Ambient fine particulate matter ($PM_{2.5}$) is measured in micrograms per cubic meter (μg/m³). The downwind exposure index is the inverse-hyperbolic-sine-transformed wildfire exposure measure constructed from fires of at least 100 acres within 500 km and weighted by fire acreage, wind alignment toward the ZIP Code, and distance decay. Any downwind exposure equals one when the ZIP Code has positive downwind wildfire exposure in a given month and zero otherwise. Temperature is the number of days in the month with maximum temperature at or above 80°F; precipitation is measured in millimeters; and wind speed is measured in meters per second. Fire-acreage measures report thousands of acres burning within 0–25 km, 25–100 km, and 100–500 km of the ZIP Code. Population is measured in thousands of residents. Share Black, non-Hispanic, share Hispanic, share aged 0–2, and poverty rate are measured as percentages of the ZIP Code population.

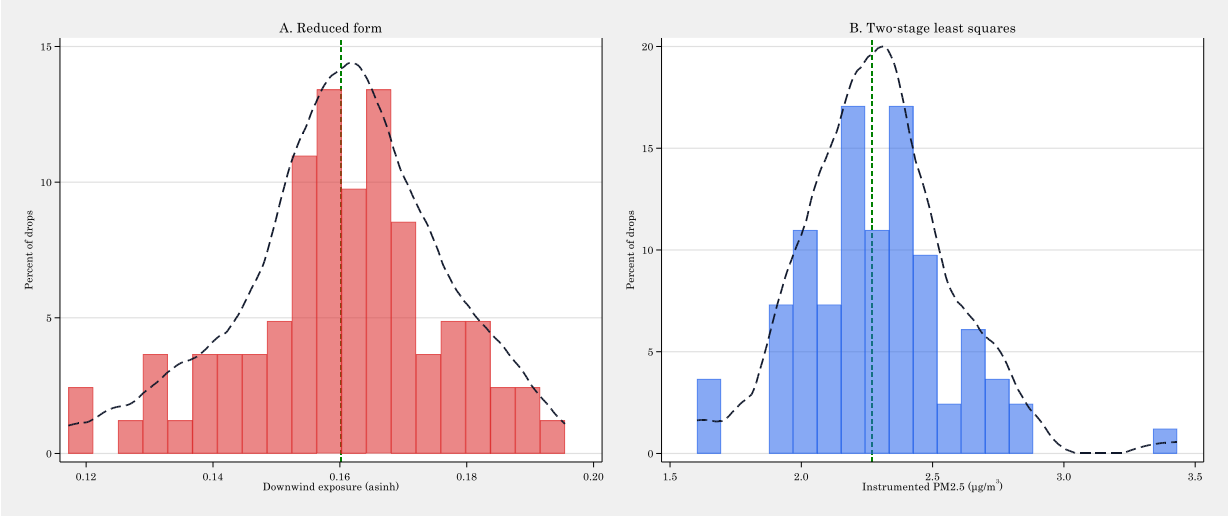
Robustness Checks

To assess whether a single large wildfire event, geographic area, or time period drives the main result, we conduct two leave-one-out robustness tests. The first re-estimates the model 2,140 times, each time excluding one geographic unit, defined as a city or county, and examines the distribution of the resulting coefficients. The second follows the same approach but instead excludes one calendar year-month at a time from the full sample. The resulting estimates remain consistently positive and closely centered around the full-sample estimate, indicating that our main finding is not driven by any single geographic area or month with unusually large wildfire activity.



Appendix Figure A2. Leave-One-Out Robustness across All City and County Units

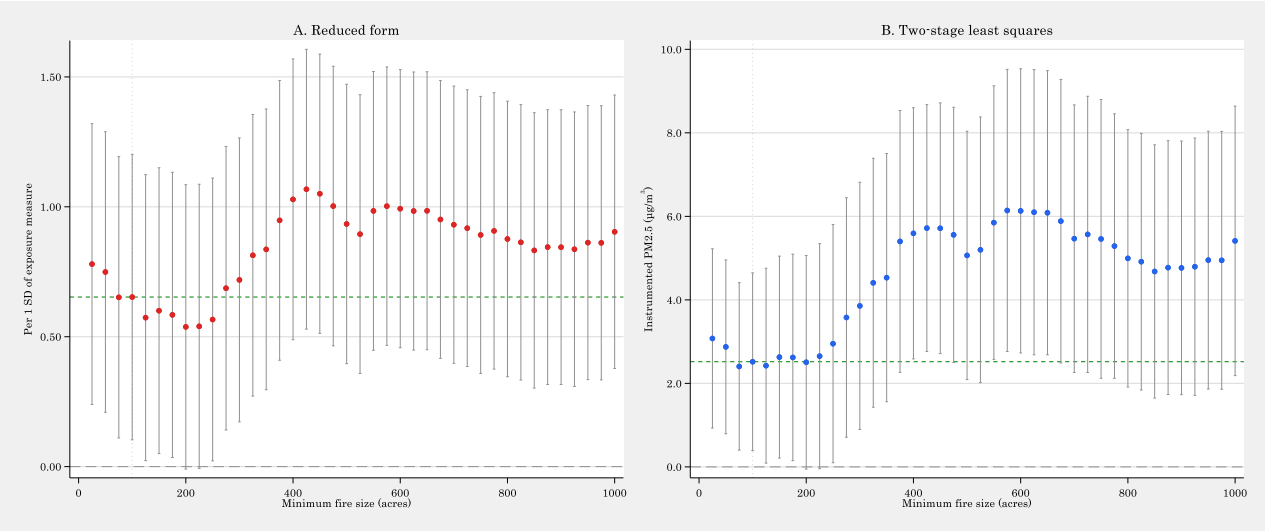
Notes. Histograms show the distribution of estimates obtained by re-estimating the preferred model 2,140 times, each time excluding one geographic unit; a geographic unit is defined as a city or county, whichever contains fewer sample ZIP Code-months. The vertical dashed line marks the corresponding full-sample estimate, and the dashed curve shows the distribution of the leave-one-out estimates. Panel A reports reduced-form estimates of the effect of X, the inverse-hyperbolic-sine-transformed downwind wildfire exposure index, on monthly Medicaid spending measured as 100 × log. Panel B reports two-stage least squares estimates of the effect of ambient fine particulate matter ($PM_{2.5}$), measured in micrograms per cubic meter (μg/m³) and instrumented by X. The sample covers ZIP Code-months in 11 western states (Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, and Wyoming) from January 2018 through October 2024; November and December 2024 are excluded because of incomplete claims. All specifications include ZIP Code × calendar-month and Year-Month fixed effects and controls for the number of days with maximum temperature at or above 80°F, precipitation, wind speed, and the inverse hyperbolic sine of wildfire acreage in five distance bands (0–25, 25–50, 50–100, 100–250, and 250–500 km). Observations are weighted by 2020 ZIP Code population, and standard errors are clustered by ZIP Code × calendar-month. X is constructed from wildfires of at least 100 acres within 500 km and weighted by fire acreage, wind alignment toward the ZIP Code, and distance decay.



Appendix Figure A3. Leave-One-Out Robustness across Year-Months

Notes. Histograms show the distribution of estimates obtained by re-estimating the preferred model 82 times, each time excluding one calendar year-month from the sample. The vertical dashed line marks the corresponding full-sample estimate, and the dashed curve shows the distribution of the leave-one-out estimates. Panel A reports reduced-form estimates of the effect of X, the inverse-hyperbolic-sine-transformed downwind wildfire exposure index, on monthly Medicaid spending measured as 100 × log. Panel B reports two-stage least squares estimates of the effect of ambient fine particulate matter ($PM_{2.5}$), measured in micrograms per cubic meter (μg/m³) and instrumented by X. The sample covers ZIP Code-months in 11 western states (Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, and Wyoming) from January 2018 through October 2024; November and December 2024 are excluded because of incomplete claims. All specifications include ZIP Code × calendar-month and Year-Month fixed effects and controls for the number of days with maximum temperature at or above 80°F, precipitation, wind speed, and the inverse hyperbolic sine of wildfire acreage in five distance bands (0–25, 25–50, 50–100, 100–250, and 250–500 km). Observations are weighted by 2020 ZIP Code population, and standard errors are clustered by ZIP Code × calendar-month. X is constructed from wildfires of at least 100 acres within 500 km and weighted by fire acreage, wind alignment toward the ZIP Code, and distance decay.

The final robustness check varies the minimum fire size entering the exposure index. Looking straight to the two-stage least squares result, we see that reducing the minimum fire size does not meaningfully change the main estimate, and increasing the minimum fire size actually increases the point estimate. We thus consider our exposure index to be a conservative estimate of smoke-induced Medicaid expenditures.



Appendix Figure A4. Sensitivity to the Minimum Fire Size Entering the Exposure Index

Notes. Points show coefficient estimates from 40 separate re-estimations in which the minimum fire size entering the downwind wildfire exposure index is varied from 25 to 1,000 acres in 25-acre increments; vertical lines show 95% confidence intervals. The vertical dotted line marks the 100-acre threshold used in the preferred specification, and the horizontal dashed line marks the corresponding baseline estimate. Panel A reports reduced-form estimates of the effect of downwind wildfire exposure on monthly Medicaid spending, measured as 100 × log. Because the scale of the exposure index changes with the minimum fire-size threshold, Panel A reports effects for a one-standard-deviation increase in the exposure measure at each threshold. Panel B reports two-stage least squares estimates of the effect of ambient fine particulate matter ($PM_{2.5}$), measured in micrograms per cubic meter ($\mu g/m^3$) and instrumented by the corresponding downwind exposure index, on monthly Medicaid spending. The estimation sample is held fixed at 226,301 ZIP Code-months across all thresholds and covers 11 western states (Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, and Wyoming) from January 2018 through October 2024; November and December 2024 are excluded because of incomplete claims. All specifications include ZIP Code × calendar-month and Year-Month fixed effects and controls for the number of days with maximum temperature at or above 80°F, precipitation, wind speed, and the inverse hyperbolic sine of wildfire acreage in five distance bands (0–25, 25–50, 50–100, 100–250, and 250–500 km). Observations are weighted by 2020 ZIP Code population, and standard errors are clustered by ZIP Code × calendar-month

Declarations

Data availability

The data used in this study are publicly available. Medicaid spending data are from the U.S. Department of Health and Human Services Medicaid Provider Spending by HCPCS dataset. Wildfire records are from the National Interagency Fire Center InFORM Fire Occurrence Data Records and the Fire Program Analysis Fire-Occurrence Database. Ambient $PM_{2.5}$ data are from the SatPM V6.GL.03 dataset, weather data are from gridMET, provider-location data are from the Centers for Medicare & Medicaid Services National Plan and Provider Enumeration System, and population and demographic data are from the U.S. Census Bureau. Additional details on data sources and construction are provided in the Methods.

Code availability

Code used to construct the wildfire exposure measures, process the data, estimate the models, and reproduce the tables and figures will be made publicly available in a permanent repository upon publication. Code will be available to editors and reviewers upon request during the review process.

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Author contributions

H.N. and T.R. conceived the study, developed the research design and methodology, interpreted the results, and wrote and revised the manuscript. H.N. assembled and processed the data, conducted the statistical analyses, and produced the figures and tables. Both authors approved the final manuscript.

Competing interests

The authors declare no competing interests.

Ethics declaration

Not applicable.