Medicaid Enrollment Responses to Wildfire Pollution

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Abstract

This paper leverages plausibly exogenous variation in wildfire-driven ambient particulate matter (wildfire-PM) to estimate its causal effect on health insurance enrollment in the United States. I combine self-reported enrollment data from the American Community Survey with wildfire-PM estimates from Childs et al. (2022) and exploit within-area, temporal variation in wildfire-PM to identify its effect on insurance enrollment. The results indicate that wildfire-PM exposure significantly increases health insurance enrollment, driven entirely by Medicaid. The expansion of Medicaid under the Affordable Care Act (ACA) appears to reduce Medicaid enrollment responses to wildfire-PM in states that chose to expand eligibility. Using county-level mortality rates and variation in state-level Medicaid expansion status, I show evidence that Medicaid may be mitigating health damages associated with wildfire pollution.

1 Introduction

Wildfires pose a growing threat to public health as they escalate and reverse air quality improvements in some parts of the U.S. (Burke et al., 2023). Wildfires release large amounts of fine particulate matter ($PM_{2.5}$) into the air, which can travel vast distances, infiltrate homes, and affect the health of individuals who live far from the point of origin. While the adverse health impacts of wildfire-driven $PM_{2.5}$ (hereafter wildfire-PM) are well-documented (*e.g.*, see Miller et al., 2017; Gould et al., 2023), much less is known about how individuals respond in terms of behavior to this environmental health shock, particularly in terms of insurance enrollment.

Previous literature on behavioral responses to wildfire pollution has found that higher-income individuals are more likely to stay indoors and purchase protective equipment compared to lower-income individuals (Burke et al., 2022). Financial constraints are likely responsible for the lack of adaptive behavior within low-income communities and this could be exacerbating existing disparities in exposure and subsequent health outcomes. For example, lower-income individuals tend to live in areas with lower air quality (Colmer et al., 2020) and in homes more susceptible to wildfire-PM infiltration (Krebs et al., 2021; Krebs and Neidell, 2024). My research fills an important gap in the literature by showing that Medicaid enrollment responses to wildfire-PM are a key behavioral adaptation for lower-income individuals. Furthermore, I show evidence that suggests Medicaid is reducing the mortality effects of extreme wildfire-PM exposure among lower-income individuals who often do not have the means to take other preventative actions.

This study provides the first evidence that wildfire-PM exposure increases health insurance enrollment in the U.S. through Medicaid. Leveraging within-area variation in annual average wildfire-PM exposure derived from Childs et al. (2022), I estimate the causal impact of air pollution on health insurance enrollment status using a two-way fixed effects model controlling for a rich set of individual characteristics available in the American Community Survey. The quasi-random nature of wildfire-driven air pollution allows for a credible causal estimate because unobserved factors influencing insurance enrollment are unlikely to correlate with within-area variation in wildfire-PM over time. I find that a one standard deviation increase in annual wildfire-PM exposure leads to a 1 percentage point increase in Medicaid enrollment among eligible individuals, which corresponds to a 1-2% increase relative to the average take-up rate in the Medicaid-eligible population. I show that these enrollment responses persist for a couple of years using a distributed-lag model. I show that enrollment responses are significantly affected by lagged values of wildfire-PM but not the future value.

There is significant heterogeneity in Medicaid enrollment responses by race and income within the Medicaid-eligible population. Black individuals tend to exhibit much larger enrollment responses relative to white individuals. Higher-income individuals within the Medicaid-eligible population tend to have slightly smaller enrollment responses. These differences by race and income could be reflecting unobserved heterogeneity in the dose of exposure and/or responses to exposure. For example, underlying differences in health endowment, investments in health, and residential/racial sorting may influence the dose-response function in a manner correlated with race or income. Local-area characteristics also play an important role. Areas with higher baseline Medicaid take-up rates experience larger enrollment responses to wildfire-PM. One explanation is that high baseline take-up rates tend to be correlated with more generous benefits and fewer barriers to enrollment (Sommers et al., 2012). I also find that areas with higher historical wildfire pollution tend to have smaller enrollment responses. This finding is consistent with prior literature and thought to be driven by more effective behavioral adaptations in high pollution areas and/or long-term sorting based on vulnerability to air pollution.

Medicaid enrollment responses to wildfire-PM exposure are muted in the years after expansion under the Affordable Care Act (ACA). I leverage the state-level variation in Medicaid expansion status to compare Medicaid enrollment responses in expansion states and non-expansion states before and after expansion. States that chose to expand experience significantly lower Medicaid enrollment responses to wildfire-PM after expansion. One potential explanation is the overall increase in enrollment due to the expansion of Medicaid resulting in increased outreach and reduced barriers to enrollment.

Mortality effects of wildfire-PM exposure are also muted in expansion states, post-expansion. I use county-level mortality rates from CDC WONDER and link them with annual wildfire-PM estimates to show that adult mortality effects are smaller after expansion in expansion states relative to non-expansion states during years with the highest levels of wildfire-PM exposure. It is important to note that other, potentially larger, mediating impacts are not captured here like reductions in morbidity and comorbidity related to wildfire-PM exposure. These results add to preexisting evidence that Medicaid expansion provided a critical safety net to low-income adults who are vulnerable to climate-related risks like increases in wildfire pollution.

This study contributes to a broader understanding of how air pollution influences health-related behaviors, including insurance decisions. The EPA's Integrated Science Assessment links exposure to $PM_{2.5}$ with adverse health outcomes ranging from respiratory issues to cardiovascular mortality (EPA, 2019). Contributions by the economics literature have identified a wider range of effects on health, behavior, and cognition (*e.g.,* Chay and Greenstone, 2003; Zivin and Neidell, 2012; Currie et al., 2014; Schlenker and Walker, 2016; Halliday et al., 2019; Bayham et al., 2022; Krebs and Luechinger, 2024). Previous literature has documented missed school days (Currie et al., 2009), reduced outdoor activities and tourism (Neidell, 2009; Zivin and Neidell, 2009; Noonan, 2014; Keiser et al., 2018; Jiang et al., 2019; Yan et al., 2019), changes in migration and reduced mobility (Banzhaf and Walsh, 2008; Cui et al., 2019; Liu and Yu, 2020), and increased purchases of face masks and filters (Zhang and Mu, 2018). Air pollution is also known to increase healthcare utilization and costs (Deryugina et al., 2019; Birnbaum et al., 2020). However, few studies have explored how individuals adjust their health insurance coverage in response to these risks.

While studies in China have found that air pollution can affect health insurance enrollment (Chang et al., 2018; Chen and Chen, 2020), the United States presents a markedly different context. In China, higher baseline pollution levels and a near-universal public insurance system with relatively low benefits create a strong demand for private supplementary coverage. This private supplementary insurance is the outcome of interest in Chang et al. (2018) who show that daily variations in the Air Quality Index influences purchases and cancellations of this type of insurance. The outcome of interest in this study is a major source of public insurance in the United States. Public insurance in China is largely compulsory and roughly 90% of the population has publicly managed insurance (Chang et al., 2018). In contrast, the U.S. health insurance system is a complex mixture of public and private options. Medicaid, a major public insurance option in the U.S., typically offers comprehensive coverage to eligible individuals at no cost with roughly 60% take-up among those eligible in my sample. Baseline pollution levels between the two countries are also very different. The average annual PM concentration in Chen and Chen (2020) was 44 μgm^{-3}, while the average was roughly 10 μgm^{-3} in the United States during the same period according to data from the U.S. Environmental Protection Agency (EPA). Therefore, my study provides insights into how a U.S.-specific environmental and policy context influences the relationship between pollution exposure and health insurance enrollment.

2 Background

2.1 Health insurance in the U.S.

Health insurance coverage in the US comes from a mixture of private and public sources covering approximately 54% and 36% of the population, respectively (Keisler-Starkey and Bunch, 2022). Employer-sponsored insurance is the largest privately-sourced insurance, while Medicaid and Medicare are the largest sources of public insurance.

Employer-sponsored health insurance plans are selected and offered to employees and their families as a benefit of employment. Typically, employers will offer insurance plans to their full-time employees (i.e., those that work at least 35 hours a week) and cover a significant portion of the insurance premium. Enrollment in employer-sponsored insurance typically occurs during an annual open enrollment period, during which employees can select or change their health plans. Migrating to a new employer and certain life events, such as marriage or the birth of a child, may trigger a special enrollment period.

Medicaid is typically free comprehensive coverage for individuals with low income. Generally, individuals and families with incomes below a certain threshold are eligible for Medicaid, and these thresholds vary by state, age, and family size. Modified adjusted gross income (MAGI) is used to determine a household's eligibility for Medicaid. Generally, MAGI is identical or very close to a household's adjusted gross income, which is used to calculate taxable income. Medicaid take-up among those who are eligible is relatively low with national estimates roughly ranging between 50% and 60% among those eligible, with much variation between states and within sub-groups (Aizer, 2003; Sommers et al., 2012; Abdus, 2024). The three often-cited reasons for the relatively low take-up rate are: a lack of knowledge about enrollment or eligibility, an inconvenient application process, and the negative stigma often associated with participation in public programs.

Medicare is a free or low-cost public insurance that is targeted to seniors who are 65 and older. In most cases, Medicare enrollment is automatic so I do not consider Medicare as an outcome for this study on enrollment decisions.

2.2 The Affordable Care Act (ACA)

The Affordable Care Act (ACA) restructured the U.S. healthcare system and increased health insurance enrollment in general. The ACA was enacted in 2010, but its main components did not take effect until 2014. Major policy changes include the expansion of Medicaid eligibility to previously ineligible adults, the creation of health insurance marketplaces to aid in the enrollment process, and the introduction of subsidies to encourage qualifying individuals to purchase insurance. The Medicaid expansion increased access to previously ineligible individuals. The expansion was initially a requirement for all states, but a 2012 Supreme Court decision allowed states to opt in. By the end of 2014, 27 states (including the District of Columbia) had expanded Medicaid eligibility[1]. A handful of states elected to opt-in over the next few years[2]. The expansion has been linked to improved health outcomes and increased access to preventive care for those covered (*e.g.,* see Guth et al., 2020). Mandates were also introduced which prohibited insurers from denying coverage based on pre-existing conditions and imposed a tax on individuals without health insurance. The tax was initially set in 2014 (the amount varied with income) and the penalty increased over time until 2019 when it was effectively set to $0. There were certain exemptions for individuals with incomes below the filing limit, lack of affordable coverage options, or other hardships (Jost, 2013; Keith, 2018).

3 Data

3.1 American Community Survey

I use the American Community Survey's Public Use Microdata (ACS) for self-reported health insurance enrollment and detailed individual-level characteristics. This survey can support estimates for subgroups of the population and small geographic areas because of its large, representative sample (Turner and Boudreaux, 2010). The smallest identifiable geographical unit in the ACS are named Public Use Microdata Areas (PUMAs). These PUMAs are delineated based on population within states and along census tracts after each decennial census. Due to the time-varying delineation of PUMAs, I use survey data from 2012-2019 when PUMA boundaries remain constant and are based on the 2010 decennial census. PUMAs tend to be geographically smaller than counties in densely populated areas and larger than counties in sparsely populated areas. Figure 1 compares PUMA and county delineation.

The ACS is the only national survey that continuously provides sub-state level data on health insurance enrollment. The survey asks respondents if they are currently covered by any of the listed sources of health insurance and the respondent must answer yes or no to each source. This gives access to specific sources of coverage and whether they are private or public. I only investigate effects on the largest private and public sources, employer-sponsored insurance and Medicaid. The sources of coverage are not mutually exclusive

[1] DE, MA, NY, VT, and DC all expanded Medicaid prior to the ACA (Miller et al., 2021).

[2] AK, PA, IN, LA, MT, VA, ME all expanded Medicaid between 2015 and 2019.

and the Census Bureau applies logical coverage edits to address Medicaid underreporting (Lynch et al., 2011). ACS insurance enrollment estimates are generally consistent with administrative data and other national surveys but Medicaid enrollment tends to be understated (Boudreaux et al., 2011, 2015). There is also evidence that the Medicaid undercount has worsened in Medicaid expansion states post-ACA (Boudreaux et al., 2019).

I focus on individuals in the civilian, non-institutional population who are likely required to enroll themselves into health insurance. This means that they should no longer have the option to use their parent's insurance or be eligible for Medicare. Young adults are allowed to remain on their parents' insurance plans until age 26 and Medicare coverage generally begins at age 65. Furthermore, I exclude individuals who recently moved into their home to ensure that they experience the local wildfire pollution in a given year and to minimize the impact of short-term migration patterns that may be influenced by wildfires. However, results are similar whether I include or exclude these individuals (results available upon request). This restricts the sample to adults aged 27 to 64 years of age between 2012-2019 who have lived in their current home for at least one year.

Eligibility for Medicaid is not collected as part of the ACS, therefore, I approximate eligibility for Medicaid using two methods. I approximate eligibility using household income information from the ACS and state-level eligibility thresholds from the Kaiser Family Foundation (KFF). As a sensitivity check for the main results, I also approximate eligibility by following Heim and Lin (2017) and Soni et al. (2017). This process involves using ACS interrelationship variables to identify family units and use detailed individual income data to estimate modified adjusted gross income (MAGI) for each taxable family unit. I calculate MAGI as the total family income net supplemental security income and public assistance payments. I then calculate income as a percent of the federal poverty level (FPL) using annual poverty guidelines from the United States Department of Health and Human Services. Finally, I compare the estimated MAGI to state-level eligibility thresholds from the Kaiser Family Foundation (KFF) to determine eligibility.

3.2 Wildfire-PM

Childs et al. (2022) predicts daily wildfire-PM using a robust machine learning model with inputs from ground, satellite, and meteorological data. Fire locations, satellite-based smoke plume detection, and derived trajectories from the point-of-origin all help to inform on the presence of wildfire smoke above an EPA monitor station. When wildfire smoke is present above an EPA monitor station, wildfire-PM is inferred as the PM exceeding the non-smoke median value for the station-month. A machine learning model uses remotely sensed cross-sectional and time-varying covariates to make daily predictions on a 10×10 km^2 grid for the contiguous United States from 2006-2020. The model performs well with both the observed PM data from EPA monitors and an external data source from PurpleAir[3]. Furthermore, Ma et al. (2024) shows that the wildfire-PM estimates from

[3]PurpleAir is a company that sells affordable air quality sensors to residential and commercial customers and creates a network of sensors that provides publicly accessible data on air quality.

Childs et al. (2022) are consistent with an alternative approach used by Aguilera et al. (2023) for California[4].

Following code provided by Childs et al. (2022), I aggregate wildfire-PM concentrations up to the PUMA-day using a population-weighted average. Then, I average daily wildfire-PM values for each PUMA-year. Shapefiles for PUMA boundaries are from IPUMS USA and population estimates are from WorldPop. Figure 2 visualizes the spatiotemporal variation in wildfire-PM I leverage in this study. This figure displays the annual population-weighted average wildfire-PM for each PUMA. The darkest areas, which indicate the highest annual average concentrations, are clustered in the northwestern US. However, there are also moderately high levels of smoke that permeate past the Rocky Mountains and into the Midwest. Record setting fires in 2017 substantially increased wildfire-PM in northwestern PUMAs between Northern California and British Columbia. Wildfire-PM also increased in 2016 for a smaller number of southeastern PUMAs during the Gatlinburg wildfires in Tennessee.

3.3 Summary statistics

Summary statistics are displayed in table 1. The average wildfire-PM concentration is approximately 0.4 $\mu g/m^3$. The average age is 46 years old and the average individual has an income of about 340% FPL. Approximately 70% of individuals self-identified as non-Hispanic White, 10% identified as non-Hispanic Black, and 13% identified as Hispanic. About 44% of respondents have graduated with a college degree while 10% have no high school degree. I also calculate these statistics for the Medicaid eligible population where eligibility is approximated using the two methods discussed in Section 3.1.

Medicaid take-up among those eligible is slightly higher when using ACS income to infer eligibility. The take-up rate is 55% when using MAGI and 59% when using ACS income. Average annual Wildfire-PM is nearly identical across both methods and the full sample. The percentage of White individuals falls from 71% in the full sample to 57% for both Medicaid-eligible samples. This is largely offset by an increase in Hispanic and Black individuals. Roughly one-fifth of the Medicaid-eligible sample completed some college degree. The majority of individuals in this sample have at most a High school degree (55%).

4 Empirical Strategy

4.1 Main specification for insurance enrollment

Although a majority of wildfires in the U.S. are caused by human activity, their occurrence is likely independent of health insurance enrollment decisions conditional on local-area and time fixed effects. This plausible exogeneity allows me to study the causal impact of air

[4] Aguilera et al. (2023) uses machine learning models to predict daily PM concentrations, statistical methods to isolate wildfire-PM, and relies on a novel imputation procedure to produce zip-code level estimates.

pollution on health insurance enrollment. I capture this relationship using the following equation:

$$Y_{ipy} = \beta PM_{p(y-1)} \; + \; X'_{ipy}\boldsymbol{\gamma} \; + \; \delta_p \; + \; \delta_y \; + \; \epsilon_{ipy} \tag{1}$$

where Y_{ipy}, the outcome of interest, is whether individual i, in PUMA p, in year y, has health insurance. $PM_{p(y-1)}$ is the annual average wildfire-PM for PUMA p in year $(y-1)$ standardized to have a mean of zero and standard deviation of one. Note that the preferred wildfire-PM measure in this study is the average wildfire-PM for the previous year. This is an attempt to align exposure with the insurance enrollment decision that likely occurred at the end of the previous year. An additional specification detailed below explores the dynamic relationship between exposure and enrollment including contemporaneous effects. The coefficient of interest β captures the effect of a one standard deviation increase in annual average wildfire-PM on the probability that an individual will have insurance in the following year. This effect is after accounting for PUMA and year fixed effects, α_p and α_y, respectively. PUMA fixed effects control for time-invariant differences across PUMAs that may be correlated with exposure and enrollment, like geographic location and urbanization. Year fixed effects control for time-varying shocks that have a common effect on all PUMAs, like the ACA's individual mandate. I also control for a vector of individual characteristics, X'_{ipy}, including age, marital status, income, and employment status. Table 1 lists all individual-level control variables.

First, I investigate the effect of wildfire-PM on the probability of having any health insurance at all. Then, I run separate regressions for employer-sponsored insurance (ESI) and Medicaid. These initial regressions include the full sample of adults aged 27-64 and do not condition on eligibility for Medicaid. I repeat these regressions conditioning on eligibility. For regressions where Medicaid is the outcome, the sample is restricted to Medicaid-eligible individuals. For regressions where ESI is the outcome, the sample is restricted to adults who are not eligible for Medicaid and work full-time (35 hours per week or more).

4.2 Binned and distributed-lag specifications

I focus on Medicaid enrollment responses after showing that they are driving the increases in health insurance enrollment. The following equation estimates a distributed lag model capturing the dynamic relationship between exposure and Medicaid enrollment:

$$Medicaid_{ipy} = \sum_{n=-1}^{3} \lambda_n PM_{p(y-n)} \; + \; X'_{ipy}\gamma \; + \; \delta_p \; + \; \delta_y \; + \; \epsilon_{ipy} \tag{2}$$

This specification includes the contemporaneous value of wildfire-PM along with three lags and one lead. I can include these measures without losing observations because the wildfire-PM data is available from 2006-2020. The outcome $Medicaid_{ipy}$ is equal to one if an individual i, in PUMA p, has Medicaid in year y. All else remains the same as in equation 1.

A third specification replaces the continuous measure of average annual wildfire-PM in equation 1 with a binned measure and is represented by equation 3. The binning procedure divides the wildfire-PM values into quintiles ensuring that each bin contains roughly 20% of total observations. The distribution of wildfire-PM values within each bin is summarized in table A.5.

$$Medicaid_{ipy} = \sum_{k=2}^{5} \alpha_k Bin^k_{p(y-1)} \; + \; X'_{ipy}\boldsymbol{\gamma} \; + \; \delta_p \; + \; \delta_y \; + \; \epsilon_{ipy} \tag{3}$$

Here, $Bin^k_{p(y-1)}$ is an indicator for average wildfire-PM in PUMA p, falling into bin k, in year $y-1$. The coefficients of interest, α_k, estimate the effect of having lived in PUMA p with a wildfire-PM concentration inside bin k, relative to the reference bin (the bottom 20% of annual average wildfire-PM values).

5 Results

The first set of regressions estimate the effect of wildfire-PM exposure on the probability of having any health insurance without conditioning on eligibility for Medicaid. Table 2a shows that wildfire-PM exposure increases the probability of having any health insurance. This increase is driven by Medicaid enrollment as shown in column 3 and there are no discernible effects on employer-sponsored insurance (ESI). Table 2b shows the next set of regressions investigating enrollment responses conditioning on eligibility for Medicaid using ACS income. Table 2c shows another set of regressions using an alternative approximation of eligibility using MAGI.

There seems to be a small increase in ESI enrollment amongst individuals who are not eligible for Medicaid and work full-time. A one standard deviation increase in annual average wildfire-PM increases the probability of an individual having ESI by a tenth of a percentage point as shown in column 1 of table 2b. For regressions where ESI is the outcome, I exclude adults who are currently enrolled in Medicaid and adults who are eligible. I also exclude adults who work less than 35 hours a week. With these exclusions, wildfire-PM exposure has a significantly positive but small effect on ESI enrollment. These estimates are similar for both methods of approximating eligibility.

Medicaid enrollment responses are the main driver of the positive effects seen in column 1 of table 2a. Column 2 of table 2b shows that a one standard deviation increase in wildfire-PM increases the probability of an eligible individual having Medicaid by about 1 percentage point, or a 1-2 percent increase relative to the average take-up rate. These estimates are similar for the different approximations of eligibility. For the remainder of the paper, I focus on the Medicaid enrollment responses in the eligible population.

5.1 Medicaid enrollment responses

The distributed-lag specification suggests that wildfire-PM exposure has both a contemporaneous and delayed effect on Medicaid enrollment. This indicates a relationship between exposure and enrollment that persists for a couple of years. The five coefficients of interest for the distributed lag model are shown in figure 3a. The point estimates on the contemporaneous measure, one-year, and two-year lag are all significantly positive falling between half a percentage point and 1 percentage point. The estimates on the three-year lag and the one-year lead are not statistically different from zero. Importantly, the magnitude on future wildfire-PM values have no significant effect on enrollment responses. The coefficient on the one-year lead has a negligible magnitude and weakly significant at the 95% level.

The results from the binned specification expressed by equation 3 does not seem to provide strong evidence of a non-linear relationship between exposure and enrollment for Medicaid. Figure 3b plots the coefficients of interest from the binned specification. The distribution of annual average wildfire-PM values are binned into quintiles and all effects are relative to the lowest quintile. Summary statistics for wildfire-PM values by quintiles are shown in table A.5. I find that the point estimates increase fairly linearly across quintiles starting at about 1 percentage point in the 2nd quintile to about 5 percentage points in the top quintile. Experiencing wildfire pollution in the middle quintile is associated with a 2 percentage point increase in probability of having Medicaid relative to years falling in the lowest quintile.

5.2 Heterogeneity by individual characteristics and local-area baseline conditions

There is significant heterogeneity in Medicaid enrollment responses by race and income, as shown in table 3. Higher-income individuals exhibit smaller enrollment responses while Black individuals exhibit larger responses relative to their counterparts. These differences suggest that income and race play a key role in shaping responses to health shocks through Medicaid enrollment. Several factors may explain these patterns. Higher-income individuals within the Medicaid eligible population may have larger health endowments or invest more towards their health, making them more resilient to health shocks. Residential sorting could also result in sub-PUMA heterogeneity in exposure and response. Previous studies have explored the income gradient on environmental damages, but the reasons for this disparity (whether dominated by differences in exposure or vulnerability) remains unclear (Hsiang et al., 2019; Colmer et al., 2020). Similar logic can be applied to the racial disparities in Medicaid enrollment responses to exposure. Black communities may be more vulnerable to wildfire-PM health shocks and/or exposed to higher levels of baseline pollution. These findings are consistent with previous research showing that Black infant mortality is particularly sensitive to changes in air pollution (Chay and Greenstone, 2003). These results also hint at environmental justice concerns regarding the unequal burden of health damages from wildfire pollution exposure.

PUMAs with higher baseline Medicaid take-up rates tend to experience larger enrollment responses. To test if baseline PUMA-level take-up rates influence enrollment responses, I interact annual average wildfire-PM with baseline Medicaid take-up rates which are calculated for each PUMA in 2012. The coefficient on baseline Medicaid take-up rates in column 1 of table 4 is positive and statistically significant indicating that a one standard deviation increase from average baseline Medicaid take-up rates is associated with an increase in Medicaid enrollment responses by 0.8 percentage points. These estimates are similar when approximating eligibility using the alternative MAGI-eligible method in table A.3. One likely reason for this finding is that take-up rates are positively correlated with coverage benefits, and ease of enrollment (Sommers et al., 2012).

Areas with higher historical wildfire-PM exposure tend to have smaller enrollment responses. To test whether higher historical wildfire-PM exposure is associated with smaller enrollment responses, I interact annual average wildfire-PM with the average annual wildfire-PM from 2006-2011 calculated for each PUMA. I find that PUMAs with higher historical wildfire-PM tend to have smaller Medicaid enrollment responses. This finding is consistent with other literature studying the health impacts of wildfire pollution (*e.g.*, Miller et al., 2017; Heft-Neal et al., 2022) and air pollution more generally (*e.g.*, Deryugina et al., 2021). Column 2 of table 4 shows that a one standard deviation increase in historical wildfire-PM is associated with lower Medicaid enrollment responses by 0.2 percentage points for average wildfire-PM levels. These estimates are similar when approximating eligibility using the alternative MAGI-eligible method in table A.3. Some possible explanations that have been brought up in previous literature include less adaptive behavior in areas with less frequent exposure and vulnerable populations sorting into areas with less historical exposure.

5.3 Enrollment responses and Medicaid expansion

The Affordable Care Act (ACA) significantly restructured the US healthcare system aiming to increase overall enrollment. Therefore, it is possible that Medicaid expansion under the ACA has significant effects on the exposure-enrollment relationship. Here, I examine whether the exposure-enrollment relationship changed in states that expanded Medicaid as part of the ACA by exploiting state-level variation in Medicaid expansion status over time.

$$\begin{aligned} Medicaid_{ipy} = \beta_1 PM_{p(y-1)} \ + \ & \beta_2(Expanded_s \times PM_{p(y-1)}) + \\ & \beta_3(Post_y \times PM_{p(y-1)}) \ + \ \beta_4(Expanded_s \times Post_y) + \\ & \beta_5(Expanded_s \times Post_y \times PM_{p(y-1)}) \ + \ X'_{ipy}\gamma \ + \ \delta_p \ + \ \delta_y \ + \ \epsilon_{ipy} \end{aligned} \tag{4}$$

The only changes from equation 1 are the inclusion of interactions between $PM_{p(y-1)}$, $Post_y$, and $Expanded_s$. $Post_y$ is an indicator for the years 2014 and onward. $Expanded_s$ is an indicator for the states that expanded Medicaid in 2014. I exclude states that expanded Medicaid before 2014 or between 2015 and 2019. The control is made up of states that did not expand or expanded after 2019. This is one approach used in Miller et al. (2021) who finds significant reductions in mortality in states that expanded Medicaid. The coefficient of interest β_5 captures a change in the exposure-enrollment relationship in expansion states across post-expansion years.

I find that enrollment responses are muted in the years following Medicaid expansion. Table 4 shows that the probability of Medicaid enrollment in response to a one standard deviation increase in wildfire-PM is 2.6 percentage points lower in expanded states after expansion relative to before expansion. These estimates are similar when approximating eligibility using the alternative MAGI-eligible method in table A.3. One potential explanation is the overall increase in enrollment that occurred due to Medicaid expansion. After states expanded Medicaid, many previously ineligible individuals will enroll for reasons unrelated to wildfire pollution. There was also the "welcome mat" effect where many previously eligible individuals enrolled due to increased outreach and/or reduced barriers to enrollment (Frean et al., 2017). Therefore, the relationship between wildfire-PM exposure and Medicaid enrollment decisions may have become less pronounced in the post-expansion years.

6 Discussion

6.1 Mechanism

I argue, like Chang et al. (2018), that negative health shocks increase the perceived value of health insurance which encourage previously uninsured individuals to enroll. Evidence from prior literature suggests that health shocks from air pollution disproportionately burden low-income communities. We may also expect to see that uninsured individuals are particularly sensitive to these health shocks. To explore this, I expand on findings from Qiu et al. (2024) with a heterogeneity analysis on county-level mortality effects based on the following baseline characteristics: proportion of low-income adults and proportion of uninsured adults. These baseline characteristics are calculated for each county using 5-year 2013 ACS estimates. Mortality rates are gathered from CDC WONDER for the years 2006-2019. Data are based on death certificates containing a single underlying cause of death and up to twenty additional multiple causes. I gather mortality rates for the following underlying causes of death: diseases of the circulatory or respiratory system (UCD-ICD-10 codes I00-I99 and J00-J98).

Mortality effects of wildfire-PM are modeled by the following equation:

$$Mortality_{cy} = \sum_{k=2}^{5} \eta_k Bin_{cy}^{k} \ + \ \delta_c \ + \ \delta_{sy} \ + \ \epsilon_{cy} \tag{5}$$

where $Mortality_{cy}$ is the age-adjusted all-cause mortality rate per 100,000 for adults aged 25-64 in county c in year y. Following Qiu et al. (2024), all regressions include county (δ_c) and state-by-year (δ_{sy}) fixed effects with standard errors clustered at the county level. All regressions are weighted by the total population aged 25-64 in 2013. Bin_{cy}^{k} is a dummy equal to one if wildfire-PM in county c in year y falls into bin k (of the five bins derived by splitting the distribution of wildfire-PM values into quintiles). The omitted bin is the first quintile (i.e., the bottom 20% of wildfire-PM values). The estimates from this baseline model are shown in the first panel of figure 4 labeled "Baseline".

To investigate heterogeneity in mortality effects by county-level uninsured rates and low-income rates, I interact these baseline rates with the binned wildfire-PM measure:

$$Mortality_{cy} = \sum_{k=2}^{5} \eta_k Bin_{cy}^k + \sum_{k=2}^{5} (\theta_k Bin_{cy}^k \times Lowincome_c) + \delta_c + \delta_{sy} + \epsilon_{cy} \quad (6)$$

$$Mortality_{cy} = \sum_{k=2}^{5} \eta_k Bin_{cy}^k + \sum_{k=2}^{5} (\rho_k Bin_{cy}^k \times Uninsurance_c) + \delta_c + \delta_{sy} + \epsilon_{cy} \quad (7)$$

where $LowIncome_c$ and $Uninsurance_c$ are rates calculated for the adult population aged 25-64 in county c. Both rates are calculated using 2013 5-year ACS estimates via the *tidycensus* package in R. Low income is defined as having income less than 150% of the Federal Poverty Line (FPL). Uninsured rates and low income rates are standardized to have a mean of zero and standard deviation of one.

Figure 4 shows the total effect on mortality rates for binned wildfire-PM exposure. The baseline results show that adult mortality rates increase across wildfire-PM bins. The next two panels in the figure suggest that lower-income counties and counties with more uninsured adults are associated with slightly higher mortality rates for high levels of exposure. The increase is roughly 1-2 additional deaths per 100,000 adults when exposure falls in the highest quintile. The magnitudes are similar for lower-income and higher uninsured counties. Note that lower income counties tend to have higher mortality rates even for low-to-average wildfire-PM exposure indicating a significant disparity in wildfire-related health damages by income. The elevated mortality rate across multiple bins implies higher rates of morbidity and comorbidity related to wildfire-PM exposure. These results are in line with previous research highlighting the income gradient in environmental damages (*e.g,* Hsiang et al., 2019; Deryugina et al., 2021). This disparity in health damages may partly explain the relatively large enrollment response in the Medicaid-eligible sample.

6.2 Other explanations

Wildfire-PM might also increase the number of eligible people if exposure is associated with negative shocks to income. This means that the increase in Medicaid enrollment may be partly driven by income shocks that are correlated with increases in wildfire-PM. However, table A.2 shows that wildfire-PM is associated with small increases in income, not decreases. The first column of table A.2 shows that the probability of being eligible for Medicaid is also significantly lower following increases in wildfire-PM. These regressions include the same two-way fixed effects as the main specification but do not control for other individual characteristics. I find that a one standard deviation increase in wildfire-PM is associated with a decrease in the probability of being eligible for Medicaid in the following year. Note the increase in the probability of enrollment in table 2a in response to wildfire-PM despite the decrease in eligible individuals implied by table A.2.

One might be concerned that the composition of people in PUMA-years might be correlated with wildfire-PM exposure for many reasons (e.g., mortality, migration, survey response). The significant correlations between wildfire-PM and various respondent characteristics in table A.2 suggests that this may be occurring. To investigate changes in sample composition, table A.1 regresses various respondent characteristics on wildfire-PM exposure using two-way fixed effects without any additional controls. Table A.1 runs these regressions on the Medicaid-eligible sample and table A.2 runs these regressions on the full sample of adults. I find that certain respondent characteristics are correlated with wildfire-PM exposure. Most of these estimates have negligible magnitudes but there are a few notable relationships. Increases in wildfire-PM are associated with slight increases in the likelihood of being married, being a parent, and being employed full-time within the Medicaid-eligible population. Most of these relationships persist in regressions on the full sample. While these relationships are puzzling, given the small magnitudes of the coefficients, it is unlikely that these are driving the results. I control for a rich set of individual characteristics in all specifications assuming that any remaining differences in enrollment outcomes can be attributed to variation in wildfire-PM.

6.3 Medicaid expansion and mortality mitigation

A natural follow-up question to the main results of this study is whether Medicaid enrollment responses mitigate the mortality effects of wildfire-PM exposure. Previous research has found significant reductions in mortality in states that expanded Medicaid as part of the ACA compared to states that did not expand Medicaid (Miller et al., 2021). Here, I augment one approach used by Miller et al. (2021) to explore heterogeneity in the mortality-reducing effect by county-level wildfire-PM exposure. I estimate the following model:

$$\begin{aligned} Mortality_{cy} = &\sum_{k=2}^{5} \eta_k Bin_{cy}^k + \sum_{k=2}^{5} (\gamma_k Bin_{cy}^k \times Post_y) + \\ &\sum_{k=2}^{5} (\sigma_k Bin_{cy}^k \times Expanded_s) + \sum_{k=2}^{5} (\beta_k Bin_{cy}^k \times Post_y \times Expanded_s) + \\ &\delta_c + \delta_{sy} + \epsilon_{cy} \end{aligned} \tag{8}$$

The variables $Mortality_{cy}$ and Bin_{cy}^k are defined the same as in equations 5, 6, and 7. The variables $Expanded_s$ and $Post_y$ are defined the same as in equation 4. The coefficients of interest β_k capture the change in the exposure-mortality relationship post-expansion in expansion states relative to non-expansion states.

Figure 5 sums the coefficients from equation 8 to estimate the total effect on mortality rates for each quintile. The figure shows that counties in expansion states had significantly fewer deaths attributable to high wildfire-PM exposure after expansion. I find that Medicaid expansion is associated with roughly 6 fewer deaths per 100,000 adults for values in the highest quintile. These results expand on Miller et al. (2021) to show that

Medicaid expansion to previously ineligible adults may be reducing mortality from high levels of wildfire-PM exposure.

7 Conclusion

This paper finds a causal effect of wildfire-PM exposure on health insurance enrollment which is completely driven by Medicaid. I provide evidence that the Medicaid enrollment responses are not driven by selection nor income shocks related to wildfire-PM exposure, and this effect remains stable when using an alternative approximation of Medicaid eligibility. These Medicaid enrollment responses are relatively large and persist over time. Heterogeneity analysis shows that there are significant differences in enrollment responses across race and income within the Medicaid-eligible population. I also show evidence that areas with high baseline take-up rates and areas with historically low wildfire-PM exposure tend to experience larger enrollment responses. These findings show that Medicaid enrollment is a key behavioral adaptation among individuals who are financially constrained and disproportionately burdened by wildfire-PM exposure.

Wildfire-PM exposure causes significant health shocks and increases mortality risks, particularly in low-income communities. I argue that this health shock is driving the increases in insurance enrollment I find in the Medicaid-eligible population. Individuals who suffer health shocks are more likely to encounter hospital personnel who may facilitate enrollment. Alternatively, individuals may perceive the risks and enroll on their own without help from hospital personnel. Regardless of the procedural mechanism, low-income individuals are enrolling in Medicaid as a response to wildfire-PM exposure. This highlights Medicaid enrollment as an important behavioral adaptation available to low-income adults that is likely mitigating the health damages associated with wildfire-PM exposure.

8 Tables and Figures

Table 1: Summary statistics for wildfire-PM, Medicaid enrollment, and respondent characteristics

	(1) **Full sample** (27-64)		(2) **Medicaid-eligible** (MAGI)		(3) **Medicaid-eligible** (ACS income)	
	Mean	(SD)	Mean	(SD)	Mean	(SD)
Variables of interest						
Medicaid enrollment	0.12	(0.32)	0.55	(0.50)	0.59	(0.49)
Wildfire-PM	0.40	(0.43)	0.39	(0.48)	0.39	(0.47)
Individual Characteristics						
Age	47.71	(10.63)	45.64	(11.34)	46.37	(11.11)
Female	0.52	(0.50)	0.57	(0.49)	0.58	(0.49)
Foreign born	0.16	(0.36)	0.21	(0.41)	0.21	(0.41)
Citizen	0.93	(0.25)	0.88	(0.33)	0.88	(0.32)
Married	0.66	(0.48)	0.39	(0.49)	0.42	(0.49)
Parent	0.34	(0.47)	0.36	(0.48)	0.38	(0.48)
Unemployed	0.04	(0.19)	0.10	(0.29)	0.08	(0.28)
Not in LF	0.22	(0.42)	0.52	(0.50)	0.55	(0.50)
MAGI (% FPL)	325.44	(172.02)	80.48	(100.61)	88.32	(109.34)
ACS income (% FPL)	346.80	(158.89)	154.38	(137.86)	120.31	(117.59)
Race/Ethnicity						
White	0.71	(0.45)	0.57	(0.50)	0.57	(0.49)
Black	0.10	(0.29)	0.14	(0.35)	0.15	(0.36)
Asian	0.06	(0.23)	0.07	(0.25)	0.06	(0.23)
Hispanic	0.13	(0.34)	0.21	(0.41)	0.21	(0.40)
Native/Indigenous	0.02	(0.14)	0.04	(0.19)	0.04	(0.20)
Other race	0.04	(0.20)	0.08	(0.27)	0.08	(0.27)
Education						
Student	0.04	(0.20)	0.05	(0.23)	0.05	(0.21)
College	0.43	(0.50)	0.21	(0.41)	0.20	(0.40)
High School	0.47	(0.50)	0.55	(0.50)	0.55	(0.50)
No High School	0.10	(0.30)	0.24	(0.42)	0.25	(0.43)
Observations	9,831,427		1,342,904		1,086,394	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Unweighted averages for the full sample of adults and medicaid-eligible adults where eligibility is estimated using both MAGI and ACS income.

Table 2: The effect of Wildfire-PM on health insurance enrollment

(a) Full sample

	Any	**ESI**[1]	**Medicaid**
Wildfire-PM	0.003***	-0.000	0.004***
	(0.000)	(0.000)	(0.000)
Mean dep. var.	0.866	0.649	0.125
Percent of mean	0.4	-0.0	3.5
Observations	9,831,427	9,831,427	9,831,427

(b) Conditioning on eligibility (using ACS income)

	ESI[1]	**Medicaid**
Wildfire-PM	0.001***	0.009***
	(0.000)	(0.001)
Mean dep. var.	0.818	0.586
Percent of mean	0.2	1.5
Observations	5,831,170	1,086,394

(c) Conditioning on eligibility (using MAGI)[2]

	ESI[1]	**Medicaid**
Wildfire-PM	0.001***	0.010***
	(0.000)	(0.001)
Mean dep. var.	0.821	0.541
Percent of mean	0.1	1.8
Observations	5,785,980	1,342,904

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors at the PUMA level in parentheses. All regressions weighted using individual ACS survey weights.

[1] Employer sponsored insurance. Sample includes individuals who work full-time and are not eligible for Medicaid.

[2] MAGI is estimated by following Heim and Lin (2017); Soni et al. (2017).

Table 3: Heterogeneity in Medicaid enrollment responses by individual characteristics

	(1) Medicaid MAGI-eligible	(2) Medicaid ACS income-eligible
Wildfire-PM	0.012***	0.010***
	(0.002)	(0.002)
Age × Wildfire-PM	-0.000*	-0.000*
	(0.000)	(0.000)
Female × Wildfire-PM	0.001	0.000
	(0.001)	(0.001)
Income × Wildfire-PM	-0.002**	-0.004***
	(0.001)	(0.001)
Black × Wildfire-PM	0.009***	0.007**
	(0.002)	(0.002)
Hispanic × Wildfire-PM	-0.002	-0.001
	(0.001)	(0.002)
College × Wildfire-PM	-0.002	0.000
	(0.001)	(0.001)
No High School × Wildfire-PM	0.002	0.000
	(0.001)	(0.001)
Married × Wildfire-PM	-0.003*	-0.003
	(0.001)	(0.002)
Unemployed × Wildfire-PM	-0.002	-0.003
	(0.002)	(0.002)
Not in LF × Wildfire-PM	-0.001	-0.000
	(0.001)	(0.001)
Observations	1,342,904	1,086,394

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Individuals in the sample are Medicaid eligible adults. Clustered standard errors at the PUMA level in parentheses. All regressions weighted using individual ACS survey weights.

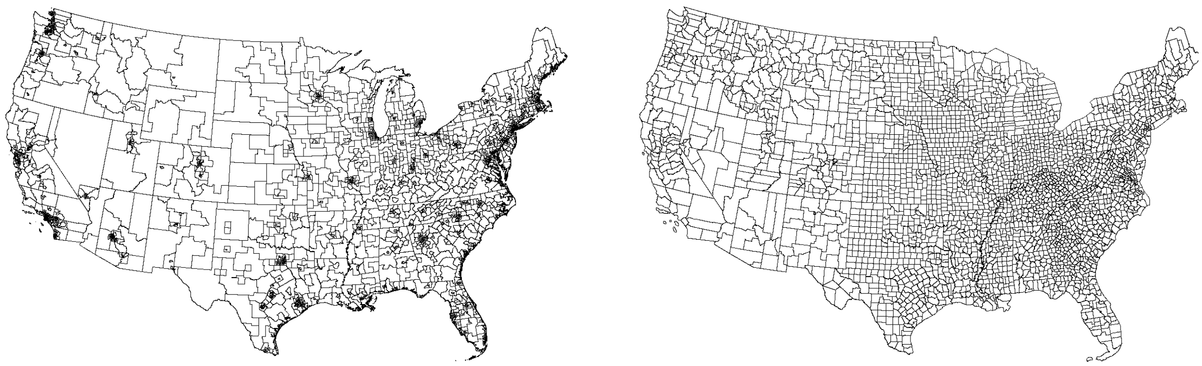
Table 4: Heterogeneity in Medicaid enrollment responses by local-area baseline conditions and post-Affordable Care Act (ACA)

	(1) Baseline take-up rate	(2) Baseline wildfire-pm	(3) Expansion states
Wildfire-PM	0.012***	0.013***	0.010***
	(0.001)	(0.001)	(0.003)
Baseline take-up × Wildfire-PM	0.008***		
	(0.002)		
Baseline wildfire-PM × Wildfire-PM		-0.002***	
		(0.000)	
Expanded × Wildfire-PM			0.030***
			(0.007)
Post2014 × Wildfire-PM			-0.010**
			(0.005)
Expanded × Post2014			0.020***
			(0.006)
Expanded × Post2014 × Wildfire-PM			-0.026***
			(0.008)
Observations	1,086,394	1,086,394	836,387

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Individuals in the sample are Medicaid eligible adults where eligibility is approximated using ACS income. Clustered standard errors at the PUMA level in parentheses. All regressions weighted using individual ACS survey weights. Baseline Medicaid take-up is defined as the percent of Medicaid-eligible individuals that were enrolled in Medicaid in 2012 and is standardized to have a mean of zero and a standard deviation of one. Baseline wildfire-PM is defined as the historical average wildfire-PM from 2006-2011 and is standardized to have a mean of zero and a standard deviation of one.

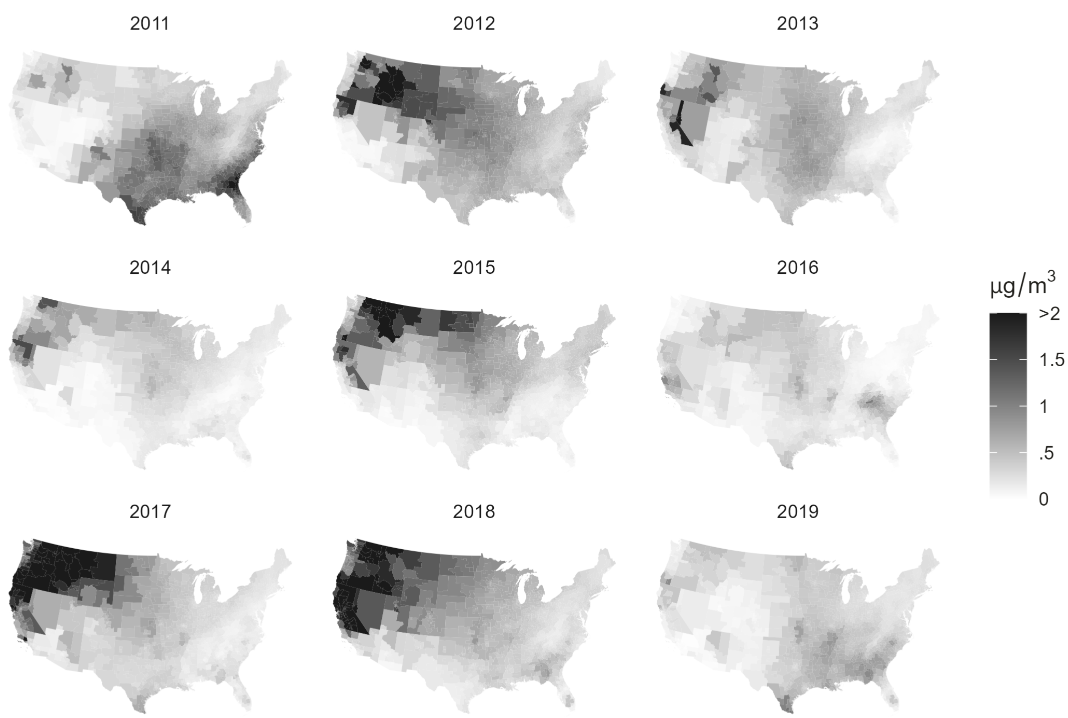
Figure 1: PUMA and county delineation

(a) PUMAs (N = 2,336) (b) Counties (N = 3,006)



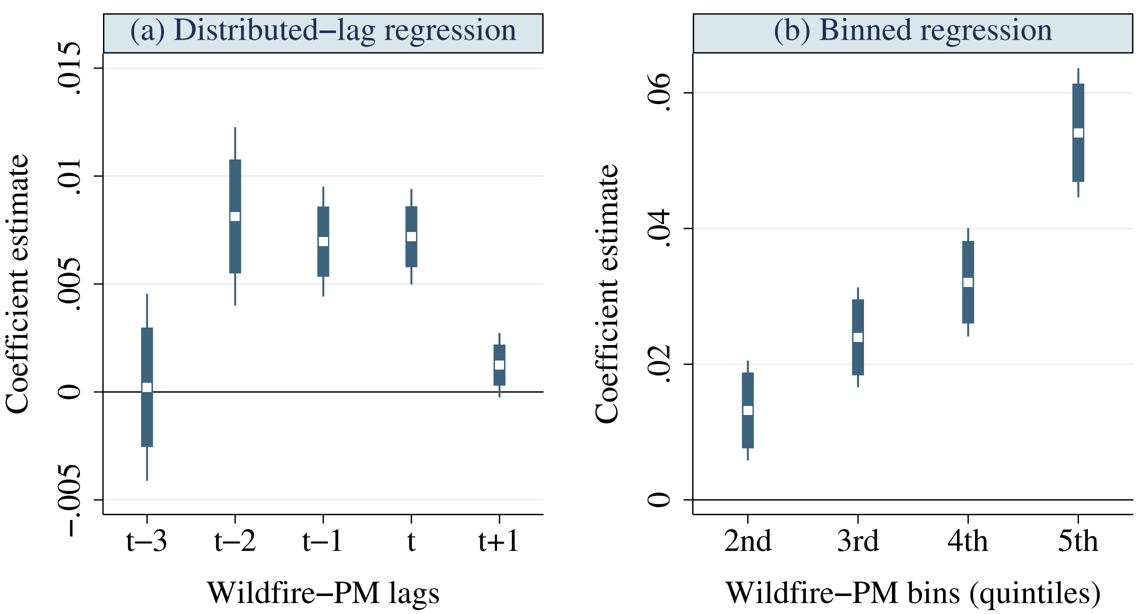
Notes: PUMA delineation based on population estimates from the 2010 census (*left*). County delinieation (*right*).

Figure 2: Annual average wildfire-PM by year



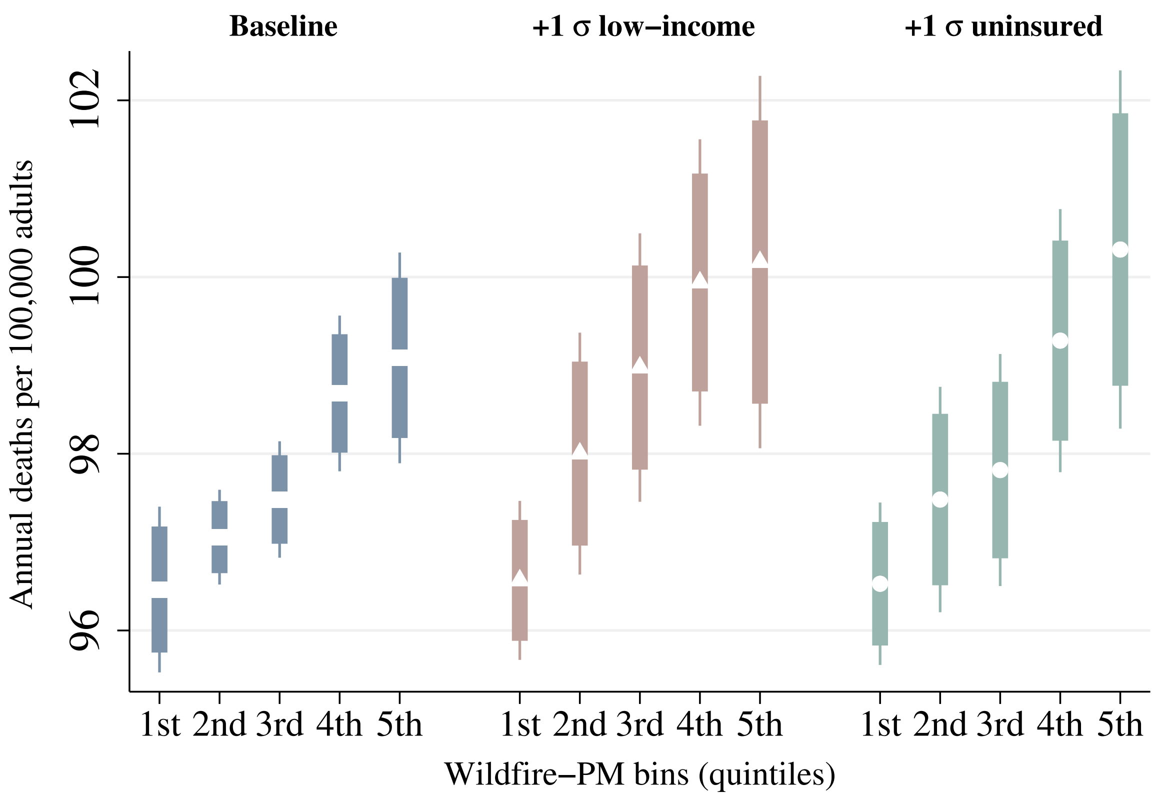
Notes: Derived from daily wildfire-PM estimates estimated by Childs et al. (2022).

Figure 3: Persistent and linear Medicaid enrollment responses



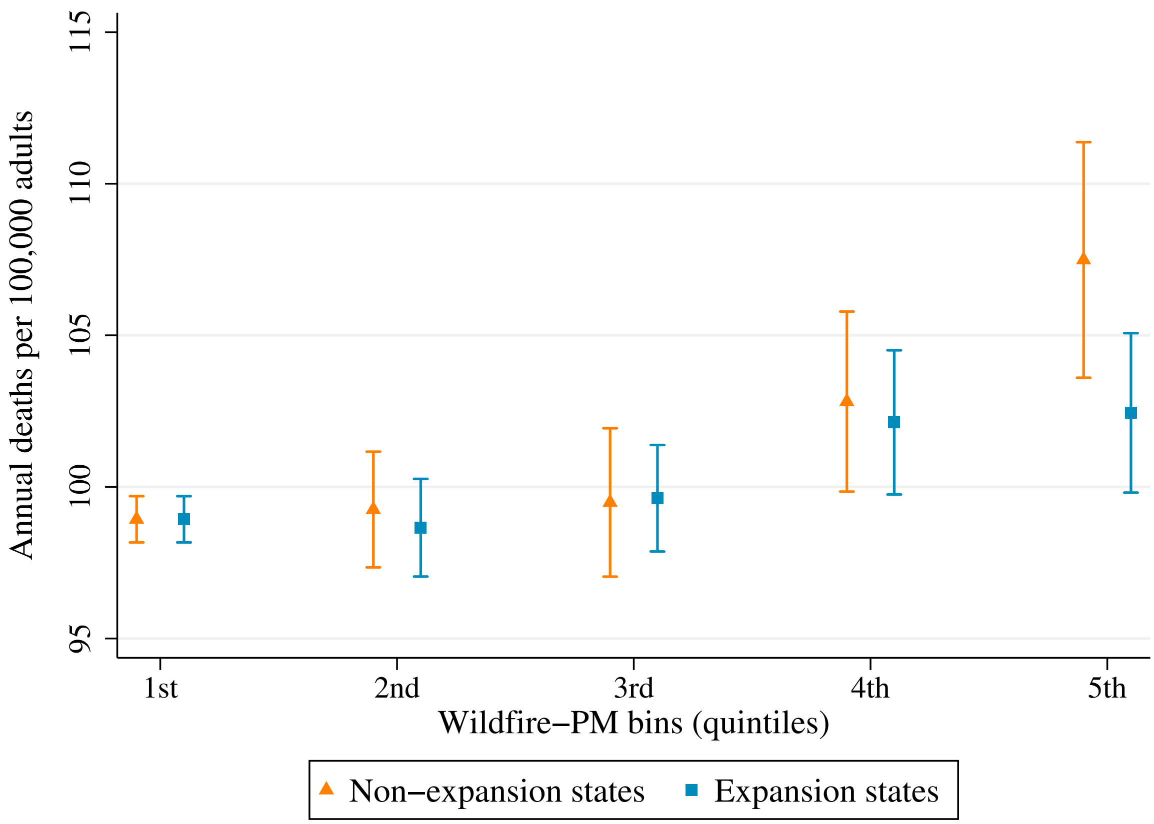
Notes: (*Left*) Coefficients are from the distributed lag model estimated in equation 2. The contemporaneous value, one-year, two-year, and three-year lagged values are displayed. Confidence intervals estimated at the 95% and 99% level. (*Right*) Results from a binned linear regression. Coefficients on each of the seven bins from equation 3 are shown with 95% and 99% confidence intervals. Effects are relative to the omitted first quintile (0–0.1 $\mu g/m^3$).

Figure 4: Heterogeneity in county-level mortality effects by baseline characteristics



Notes: Coefficients are gathered from equation 6 and 7 and summed to estimate the total number of deaths in each bin. The left panel labeled "Baseline" shows the average mortality rate for years falling within each bin. The middle panel labeled "Low income rates" shows the same mortality rates for a one standard deviation increase in baseline low income rates. The right panel labeled "Uninsured rates" shows the same mortality rates for a one standard deviation increase in baseline uninsured rates.

Figure 5: County-level mortality effects post-Medicaid expansion



Notes: Coefficients are gathered from equation 8 and summed to estimate total mortality rates for each bin estimated separately for expansion and non-expansion states after expansion.

A Appendix

A.1 Additional tables and figures

Table A.1: Selection on respondent characteristics in the Medicaid-eligible sample

	(1)	(2)	(3)	(4)	(5)
	Age	Female	Married	Parent	White
Wildfire-PM	-0.072***	0.002***	0.003***	0.007***	-0.001
	(0.015)	(0.001)	(0.001)	(0.001)	(0.001)
Mean dep. var.	44.532	0.570	0.361	0.375	0.508
Percent of mean	-0.2	0.3	0.8	1.9	-0.1
Observations	1,342,904	1,342,904	1,342,904	1,342,904	1,342,904
	(1)	(2)	(3)	(4)	(5)
	Asian	Black	Hispanic	Income (PAPL)	High School
Wildfire-PM	0.001**	0.000	0.000	1.269***	-0.001
	(0.000)	(0.000)	(0.001)	(0.212)	(0.001)
Mean dep. var.	0.065	0.173	0.248	153.157	0.249
Percent of mean	1.4	0.0	0.1	0.8	-0.2
Observations	1,342,904	1,342,904	1,342,904	1,342,904	1,342,904
	(1)	(2)	(3)	(4)	(5)
	No High School	College	Employed full-time	Employed part-time	Unemployed
Wildfire-PM	0.001	0.000	0.002***	-0.001	-0.003***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
Mean dep. var.	0.553	0.198	0.255	0.226	0.099
Percent of mean	0.1	0.0	0.9	-0.4	-2.6
Observations	1,342,904	1,342,904	1,342,904	1,342,904	1,342,904

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors at the PUMA level in parentheses. All regressions weighted using individual ACS survey weights and account for PUMA and year fixed effects. No additional controls are included.

Table A.2: Selection on respondent characteristics in the full sample

	(1) Eligible	(2) Age	(3) Female	(4) Married	(5) Parent	(6) White
Wildfire-PM	-0.001***	-0.036***	-0.000	0.001***	0.000	-0.001**
	(0.000)	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)
Mean dep. var.	0.150	46.509	0.514	0.612	0.350	0.654
Percent of mean	-0.9	-0.1	-0.0	0.1	0.1	-0.1
Observations	9,831,427	9,831,427	9,831,427	9,831,427	9,831,427	9,831,427

	(1) Asian	(2) Black	(3) Hispanic	(4) Income (PAPL)	(5) High School	(6) No High School
Wildfire-PM	0.001***	-0.001***	0.000	1.243***	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.125)	(0.000)	(0.000)
Mean dep. var.	0.061	0.121	0.163	337.401	0.113	0.474
Percent of mean	2.0	-0.5	0.1	0.4	-0.2	0.0
Observations	9,831,427	9,831,427	9,831,427	9,831,427	9,831,427	9,831,427

	(1) College	(2) Employed full-time	(3) Employed part-time	(4) Unemployed
Wildfire-PM	0.000	0.002***	-0.000**	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Mean dep. var.	0.413	0.655	0.157	0.039
Percent of mean	0.0	0.3	-0.3	-2.2
Observations	9,831,427	9,831,427	9,831,427	9,831,427

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors at the PUMA level in parentheses. All regressions weighted using individual ACS survey weights and account for PUMA and year fixed effects. No additional controls are included.

Table A.3: Heterogeneity in Medicaid enrollment responses by local-area baseline conditions and post-Affordable Care Act (ACA)

	(1) Baseline take-up rate	(2) Baseline wildfire-pm	(3) Expansion states
Wildfire-PM	0.014***	0.013***	0.005
	(0.002)	(0.001)	(0.003)
Baseline take-up × Wildfire-PM	0.010***		
	(0.002)		
Baseline wildfire-PM × Wildfire-PM		-0.002***	
		(0.000)	
Expanded × Wildfire-PM			0.041***
			(0.008)
Post2014 × Wildfire-PM			-0.005
			(0.005)
Expanded × Post2014			0.041***
			(0.005)
Expanded × Post2014 × Wildfire-PM			-0.037***
			(0.008)
Observations	1,342,904	1,342,904	1,032,342

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Individuals in the sample are Medicaid eligible adults where eligibility is approximated using MAGI. Clustered standard errors at the PUMA level in parentheses. All regressions weighted using individual ACS survey weights. Baseline Medicaid take-up is defined as the percent of Medicaid-eligible individuals that were enrolled in Medicaid in 2012 and is standardized to have a mean of zero and a standard deviation of one. Baseline wildfire-PM is defined as the historical average wildfire-PM from 2006-2011 and is standardized to have a mean of zero and a standard deviation of one.

Table A.4: Mortality effects and Medicaid expansion

	(1) Mortality rate per 100,000 adults
2nd	0.157
	(0.716)
3rd	0.245
	(1.036)
4th	-1.014
	(1.435)
5th	-2.613
	(1.775)
2nd × Post	0.166
	(1.190)
3rd × Post	0.311
	(1.761)
4th × Post	4.895**
	(2.068)
5th × Post	11.168***
	(2.485)
2nd × Expanded	-0.130
	(0.940)
3rd × Expanded	-1.737
	(1.355)
4th × Expanded	0.102
	(1.737)
5th × Expanded	1.293
	(2.065)
2nd × Post × Expanded	-0.471
	(1.586)
3rd × Post × Expanded	1.876
	(2.113)
4th × Post × Expanded	-0.787
	(2.539)
5th × Post × Expanded	-6.337**
	(3.074)
Mean dep. var.	99
Observations	17,990

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The outcome is county-level age-adjusted mortality rates for adults aged 25-64. Clustered standard errors at the county level in parentheses. Regression is weighted by total population aged 25-64.

Table A.5: Summary statistics wildfire-PM

	Mean	(SD)	Min	Max
Annual averages				
Wildfire-PM (contemporaneous)	0.36	(0.47)	0.01	8.26
Wildfire-PM (lagged)	0.39	(0.48)	0.00	8.26
Quintiles				
1st	0.07	(0.03)	0.00	0.11
2nd	0.16	(0.03)	0.11	0.22
3rd	0.28	(0.03)	0.22	0.34
4th	0.43	(0.06)	0.34	0.54
5th	0.97	(0.79)	0.54	8.26
Observations	1,342,904			

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