Up in Smoke: The Impact of Wildfire Pollution on Healthcare Municipal Finance

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ABSTRACT

We show that smoke from in-state and out-of-state wildfires is associated with higher borrowing costs in the healthcare industry, amounting to $270 million in incremental costs from 2010–2019. In California, we find underinvestment in wildfire prevention and overinvestment in wildfire suppression, suggesting that policy is partially responsible for cross-state borrowing cost externalities. These costs are disproportionately higher in high-poverty and high-minority areas where there is more uncompensated care for smoke-related illnesses. Migration sorting exacerbates these costs by concentrating vulnerable households in high-smoke counties. Our findings underline the importance of interstate coordination to prevent and suppress wildfires, and how the associated costs could be shared between states.

JEL Classification: R31, O18, N32

Keywords: Municipal Bonds, Wildfires, Air Pollution, Healthcare Finance, Externalities

I. Introduction

Large-scale wildfires have become increasingly common over the last several decades. In California alone, over 4.3 million acres were burned by wildfires in 2020, resulting in more than $19 billion in economic losses and a 15-20% surge in hospitalizations due to smoke-related illnesses (Safford et al., 2022; McCormick, 2020). Although experts project that large-scale wildfires will increase by another 50% over the next 75 years (UNEP, 2022), state-level authorities continue to underinvest in wildfire prevention (CalMatters, 2025; LA Times, 2020), raising concerns about the economic costs to not only healthcare service providers directly impacted by wildfires but also those downwind.

Environmental researchers have shown that large-scale wildfires produce drifting smoke plumes that travel hundreds of miles and reduce air quality in surrounding areas (Childs et al., 2022). For example, the Nevada Division of Environmental Protection (NDEP) has declared several air quality emergencies in response to wildfire smoke from California over the past decade. Smoke plumes from large-scale wildfires are problematic because they increase the amount of fine particulate matter ($PM_{2.5}$) in the breathable air, which can be deadly to vulnerable populations (Deryugina et al., 2019). Globally, $PM_{2.5}$ exposure is responsible for at least seven million deaths per year and is associated with low birth weight, a variety of chronic conditions such as heart disease, bronchitis, asthma, and emphysema, and more emergency room (ER) visits (Heft-Neal et al., 2023). Remarkably, wildfire smoke pollution is now responsible for about 20% of global $PM_{2.5}$ exposure, and almost 50% of $PM_{2.5}$ exposure in the Western US (UNEP, 2022).

In this study, we address important and unexplored research questions on the economics of wildfire smoke pollution. First, how does wildfire smoke pollution affect financial outcomes for healthcare service providers? The effects are not immediately clear because an increase in healthcare service demand can be profitable or unprofitable for the service provider, depending on the patient mix associated with the increased demand. For example, the average profit margin for hospital ER visits is fairly strong if the patient is privately insured (39.6%), but it is highly negative if the patient is Medicare-insured (−15.6%), Medicaid-insured (−35.9%), or uninsured (−54.4%) (Wilson and Cutler, 2014). Migration could also exacerbate these financial effects if wildfire smoke drives away higher-income residents who have the flexibility to move, or Medicare-insured residents who have lower tolerance for wildfire smoke.

Second, how does wildfire smoke pollution affect financial outcomes for out-of-state healthcare service providers, and should we classify the associated effects as externalities or just spillovers? If a state underinvests in wildfire prevention and does not compensate healthcare providers in nearby states for economic harms caused by drifting smoke plumes, then the "externality" classification is more appropriate. Given that the Environmental Protection Agency (EPA) has authority to coordinate interstate efforts to prevent and suppress large-scale wildfires, answering this question would speak directly to how the associated costs could be shared between states.

Our analysis is based on a novel combination of data sets on wildfire $PM_{2.5}$ smoke pollution from the Stanford Echo Lab, healthcare municipal bonds from Mergent, and local hospital finances from the Centers for Medicare & Medicaid Services (CMS) Healthcare Cost Report Information System (HCRIS). The first data set is based on a machine learning model from Childs et al. (2022) that uses ground, satellite, and meteorological data to identify daily wildfire smoke pollution across the US. Importantly, the data identify smoke pollution that is plausibly uncorrelated with local economic conditions, unlike EPA ground monitor data which identify smoke pollution that is partially based on local industrial pollution.

We find that wildfire smoke pollution (*Smoke*) is associated with significantly higher healthcare municipal borrowing costs. A one standard deviation increase in *Smoke* is associated with a 7.1 basis point (bps) increase in the average offering yield spread for hospitals, and a 12.1 bps increase for nursing homes. These findings are robust to the inclusion of county fixed effects, state-year fixed effects, and controls for direct physical damages from local wildfires. The yield effects correspond to $270 million in additional interest expenses for bonds issued in counties with above-mean *Smoke*. Extrapolating from current smoke trends, we predict another $585 million in interest expenses over the next ten years. These findings suggest that wildfire smoke pollution increases healthcare service demand that is unprofitable for service providers, thereby increasing their credit risk.

Out-of-state wildfire smoke is also associated with significantly higher healthcare municipal borrowing costs. Using detailed wildfire data from the US Department of Homeland Security (DHS), we decompose wildfire smoke into its in-state and out-of-state components (*HomeSmoke* and *AwaySmoke*). We find that the *AwaySmoke* effects on healthcare borrowing costs (5.8 bps for hospitals and 9.2 bps for nursing homes) are significant and slightly lower than the *HomeSmoke* effects (7.3 bps for hospitals and 14.6 bps for nursing homes). To provide a sense of economic magnitude, large-scale wildfires in California increased wildfire smoke in Nevada by 2.5 standard deviations in 2020—our point estimates suggest that an average $90 million hospital issue in Nevada in 2020 would incur an additional $1.3 million in interest expenses from this smoke pollution. These findings call for increased inter-state coordination and federal involvement to tackle the growing economic and health issues surrounding wildfires, similar to how the "Good Neighbor" provision of the Clean Air Act was meant to regulate inter-state industrial pollution prior to being blocked by the Supreme Court in 2024 (AP News, 2024*b*).

The *AwaySmoke* results suggest that state-level underinvestment in wildfire prevention imposes costly externalities on nearby states. In the case of California, the California Council on Science and Technology (CCST) notes that the state has a long history of underinvestment in wildfire prevention, and lacks a cost-benefit framework to evaluate prevention investments against suppression investments (Wara et al., 2020). A related Los Angeles Times article titled "Billions of dollars spent on fighting California wildfires, but little on prevention" argues that this problem is largely institutional, in the sense that "institutional advancement for people [in the firefighting industry in California] has to do with how well you perform the firefighting mission, not how well you reduce firefighting hazard" (LA Times, 2020). The same article notes that the state also cancelled a $100 million pilot project to improve infrastructure resiliency to wildfires, and about $155 million in funds previously earmarked for community protection and wildland fuel reduction. In combination with our findings, these results suggest that institutional and political frictions increase wildfire risk and impose costly externalities on nearby states.

Our supporting evidence suggests that California actually overinvests in wildfire suppression, perhaps as a consequence of its underinvestment in wildfire prevention. Using panel data on wildfire suppression expenditures from ten Western US state agencies that oversee wildfire suppression efforts (Cook and Becker, 2017), we find that California spends about $9,236 on wildfire suppression per burned acre, compared to an average of $680 per burned acre in the remaining states, even after controlling for wildfire intensity. We also find that the federal government pays California about $613 per burned acre for suppression efforts, compared to an average of $325 in the remaining states. These results suggest that states should establish a minimum threshold for prevention-to-suppression expenditures, similar to post-disaster spending requirements from the Federal Emergency Management Agency (FEMA) (Wara et al., 2020).

In the face of increasing wildfire risk, economists emphasize the importance of "scaling up cost-effective investments in physical protection and addressing disparities in protection and postfire recovery for socially vulnerable populations" (Boomhower, 2023; Baylis and Boomhower, 2025). In a similar vein, wildfire smoke pollution may also have a disproportionate effect on socially vulnerable populations (Banzhaf, Ma and Timmins, 2019), thereby imposing additional financial stress on local healthcare providers. In supporting cross-sectional tests, we find that the *Smoke* effects on healthcare municipal bond yields are 50% to 100% larger in high-poverty and high-minority counties, and for healthcare providers that already have weaker credit ratings and thus weaker financial positions. These results indicate that drifting wildfire smoke can also increase disparities in environmental protection for socially vulnerable populations.

Survey findings suggest that wildfire smoke is priced in the healthcare municipal bond market as long as local investors believe that wildfires will remain a permanent part of the landscape. In the municipal bond market, local investors are typically considered the marginal investors because of tax advantages associated with holding local municipal bonds. Thus, their beliefs on climate change, which are correlated with beliefs on wildfire risk (Lacroix, Gifford and Rush, 2019), likely determine if wildfire smoke is priced in the local healthcare municipal bond market, similar to how sea level rise risk is priced in the real estate market (Baldauf, Garlappi and Yannelis, 2020). To test this channel, we obtain county-level survey data from Yale University on the percentages of adults who are worried about global warming or believe that it will harm US residents (Howe et al., 2015; Marlon et al., 2022). Our results indicate that wildfire smoke effects on healthcare borrowing costs are strongest in counties where more residents believe that global warming is worrisome or harmful.

Long-run concerns about wildfire smoke are also reflected in migration patterns. Using household data from the Federal Reserve Bank of New York (FRBNY) Equifax Consumer Credit Panel (CCP), a nationally representative sample of Equifax credit report data, we find that individuals below the age of 40 with an Equifax Risk Score above 780 are more likely to move out of high-smoke counties in the long-run. The resulting patient composition thereby skews more toward Medicare-insured residents who are less likely to change addresses (US Census Bureau, 2024) and uninsured or Medicaid-insured residents who are more likely to have low credit scores, placing further stress on the finances of local healthcare providers.

Lastly, we explore how wildfire smoke affects hospital investment spending and investment sensitivity to endowment cash flow shocks. Standard Q-theory suggests that the latter variable is a useful proxy for financial constraint in the non-profit hospital setting (Adelino, Lewellen and Sundaram, 2015). Adapting the methodology in Adelino, Lewellen and Sundaram (2015), we find that a one standard deviation increase in wildfire smoke is associated with a 2.3% reduction in investment spending and a 45% increase in investment-cash flow sensitivity over two-year investment horizons. These findings suggest that hospitals respond to smoke-related financial stress by reducing their long-term capital expenditures and increasing their reliance on stock market returns to generate investment capital.

II. Related Literature

Our study contributes to several major strands of literature. First, we build on the literature on climate finance. Edmans and Kacperczyk (2022) note that the financial costs associated with climate finance stem not only from technological, political, and policy uncertainty (e.g., Bolton and Kacperczyk, 2021), but also from physical damage risk. In support of this latter channel, recent studies has shown that long-term municipal bond yields are affected by exposure to damages from rising sea levels (Painter, 2020; Goldsmith-Pinkham et al., 2023) and heat stress (Acharya et al., 2022). Additional studies similarly focus on the perceived risk of physical damage to property (e.g., Baldauf, Garlappi and Yannelis, 2020; Auh et al., 2022; Bakkensen and Barrage, 2022; Nguyen et al., 2022; Jerch, Kahn and Lin, 2023; Bakkensen, Phan and Wong, 2024). We contribute to this literature by focusing on environmental health risks from wildfire smoke, which are distinct from physical damage risks from other climate events, and the associated cost externalities for healthcare service providers.

Second, our study contributes to the literature on economic effects associated with air pollution. Burke et al. (2021) show that wildfire smoke is eroding the success of the Clean Air Act in reducing air pollution, making it difficult for municipalities to meet the US EPA's National Ambient Air Quality Standards (NAAQS). For NAAQS-incompliant counties, local municipal borrowing costs are higher due to regulatory uncertainty that the EPA may impose restrictions on industrial development (Jha, Karolyi and Muller, 2020). Additional studies show that $PM_{2.5}$ smoke pollution is associated reduced labor earnings (Isen, Rossin-Slater and Walker, 2017), weakened employment and labor force participation (Borgschulte, Molitor and Zou, 2022), decreased business activity (Addoum et al., 2023), and increased credit delinquencies (An, Gabriel and Tzur-Ilan, 2024). The healthcare industry is uniquely affected by wildfire smoke due to changes in healthcare service demand, and we provide new evidence that wildfire smoke is a costly externality for healthcare service providers that ultimately increases their borrowing costs and reduces their investment activity. Importantly, the increase in borrowing costs reduces access to credit for healthcare service providers, which has been shown to reduce the quality of healthcare services and increase hospital mortality rates (Aghamolla et al., 2024).

Third, our study contributes to the growing literature on the determinants on municipal borrowing costs. Most of the variation in municipal bond yields is attributable to default risk (Schwert, 2017), and local investors are important for pricing this risk because they are typically provided with tax advantages for purchasing in-state municipal bonds (Babina et al., 2021; Garrett et al., 2023). As a result, municipal bond yields are influenced by a variety of local factors such as pension underfunding (Novy-Marx and Rauh, 2012; Betermier, Holland and Wilkoff, 2024), opioid abuse (Cornaggia et al., 2022), remote product delivery for hospitals (Cornaggia, Li and Ye, 2024), age of the local tax base (Butler and Yi, 2022), and the presence of local newspapers for monitoring their governments (Gao, Lee and Murphy, 2020). In our study, we show that wildfire smoke is relevant not only for yields of local municipal bonds, but also for yields of municipal bonds in nearby states, as traveling wildfire smoke plumes can impose significant cost externalities on these states' healthcare systems.

Lastly, the financial health economics framework in Koijen, Philipson and Uhlig (2016) provides additional context for our findings. In their theoretical model, healthcare securities receive price discounts for two reasons: (1) a reduction in expected cash flows due to "disaster risk" stemming from potential federal regulation that cuts reimbursements to the healthcare industry, and (2) a healthcare risk premium stemming from a positive correlation between this disaster risk and tighter federal government budget constraints. In our setting, we show that there is a price discount on healthcare municipal bonds due to the "disaster risk" associated with wildfire smoke. Given that wildfire smoke tends to be localized to certain regions, the discount likely represents a reduction in expected cash flows, as local healthcare service providers have to absorb more unprofitable demand for healthcare services. However, part of this price discount may also reflect a wildfire smoke risk premium since the federal government is less likely to provide states with wildfire aid when it has tighter budget constraints, especially given that wildfires have become increasingly common across all regions in the US.

III. Data

A. *Municipal Bonds*

We collect data on municipal bonds issued in 2010–2019 from the Mergent Municipal Bond Securities Database. For each bond, we collect its offering yield, use of proceeds code, number of years until maturity, bond size, credit ratings from Moody's and S&P (rated on a scale from 1 to 21, with higher numbers representing higher-quality credit ratings), and indicator variables for whether the bond is insured, general obligation, callable, and issued in the negotiated market. Importantly, the use of proceeds code allows us to categorize bonds into three categories: (1) hospital bonds, (2) nursing home bonds, and (3) the remaining non-healthcare bonds. We also calculate the offering yield spread, a central outcome variable in our empirical analysis, by subtracting the coupon-equivalent risk-free rate from the offering yield.[1] Lastly, we aggregate our observations to the issue level. In particular, for issue size, we calculate the total size across bonds within each issue, and for the remaining variables, we calculate the size-weighted average across bonds within each issue.

We supplement the Mergent database with data from Bloomberg on the US county associated with each issue. The US county information is crucial for our analysis because it allows us to merge the municipal issue data with county-level wildfire smoke pollution

[1] Following Longstaff, Mithal and Neis (2005), the coupon-equivalent risk-free rate is calculated as follows. First, for each municipal bond, we calculate the present value of its future payments using the risk-free yield curve from Gürkaynak, Sack and Wright (2007) to obtain its risk-free price. Second, we calculate the yield-to-maturity on the municipal bond using its payment schedule and the risk-free price to obtain its coupon-equivalent risk-free rate.

data. We also supplement the Mergent database with county demographic data from the US Census Bureau's American Community Survey. Lastly, following other municipal bond studies, we exclude outlier municipal bond records where (1) the maturity is over 100 years, (2) the offering yield exceeds 50 percentage points, (3) the coupon rate is variable or zero, (4) the issue is not exempt from federal taxes, (5) the bond was issued outside of the continental US, where wildfire smoke pollution information is not available.

Table I reports summary statistics for our samples of non-healthcare issues (Panel A), hospital issues (Panel B), and nursing home issues (Panel C). The non-healthcare issues comprise 93.6% of the sample by total issue size. These issues have a mean offering yield spread of 31.6 bps, issue size of $22 million, maturity of 8 years, and rating number of 18.4 (approximately Aa3 on the Moody's credit rating scale). By contrast, hospital and nursing home issues generally have higher risk profiles. They have higher average offering yield spreads, lower credit ratings, larger issue sizes, and longer maturities. These issues are also less likely to be general obligation or insured and more likely to be callable or issued in the negotiated market. In our later tests that examine the effects of wildfire smoke on offering yield spreads for hospital and nursing home issues relative to non-healthcare issues, we control for these differences in issue characteristics.

B. Wildfire Smoke Pollution

We obtain wildfire smoke pollution data at the daily census tract level from the Stanford Echo Lab. The data feature the predicted level of surface $PM_{2.5}$ concentrations from wildfire smoke plumes. Childs et al. (2022) construct the smoke pollution measure using a machine learning algorithm that detects anomalous variations in $PM_{2.5}$ concentrations on days when smoke is likely in the air. Their approach combines ground monitor $PM_{2.5}$ readings from

EPA monitoring stations with satellite imagery from the National Oceanic and Atmospheric Administration (NOAA) Hazard Mapping System (HMS) and air trajectories from known fires from the NOAA Air Resources Laboratory. For each ten-kilometer grid and day, they calibrate the smoke $PM_{2.5}$ predictions using: (1) distance to the closest fire clusters, (2) mean eastward wind speeds, (3) mean westward wind speeds, (4) mean air and dewpoint temperatures at two meters from the ground, (5) total precipitation, (6) sea-level and surface pressure, (7) planetary boundaries, and (8) land use and elevation. As a result, the predicted smoke $PM_{2.5}$ measure excludes all the variation from non-wildfire factors such as industrial pollution, road density, dust, and elemental carbon (Childs et al., 2022).

To examine the impact of population exposure to wildfire smoke pollution on municipal bond yields, we aggregate the smoke pollution predictions from Childs et al. (2022) to the county-year level in two ways. Our first and central approach is to calculate the population-weighted annual cumulative $PM_{2.5}$ exposure across census tracts within each county, where population shares are pegged to the 2014 American Community Survey (ACS) population estimates. Our second approach is to calculate the percentage of days in each year that a county had a "smoke day," defined as a county-day in which at least 75% of the census tracts had a smoke $PM_{2.5}$ concentration above zero.

We observe significant time-series and cross-state variation in wildfire smoke pollution. In particular, Table II and Figure 1 provide summary statistics of our wildfire smoke pollution metrics by year. These statistics indicate that wildfire smoke pollution has been steadily trending upward over time, with large spikes during some years that double wildfire smoke pollution from previous years. Figures 2 and 3 illustrate the geographic variation in annual cumulative smoke exposure and smoke days over time. To get a sense of relative changes over time, the former variable is standardized by subtracting its mean from 2006–2009 and then dividing the difference by its standard deviation from 2006–2009. The figures indicate that wildfire smoke pollution was concentrated in the Midwest during the early part of the decade, but has since shifted to the Western US, with an exposure intensity spilling over to many states in other regions.

Lastly, Figure 4 maps the decennial change in the average population-weighted cumulative smoke $PM_{2.5}$ exposure by county, where decennial change is the average value of this smoke measure in 2016–2020 minus its average value in 2006–2010. This figure indicates that cumulative smoke exposure has increased throughout most of the country. The greatest changes in wildfire smoke levels are observed in the Western US, where the annual smoke pollution exposure level reached a maximum $PM_{2.5}$ concentration of about 1,700$\mu g/m^3$. By contrast, counties along the Eastern seaboard have experienced a slight decline in wildfire smoke exposure.

IV. Wildfire Smoke and Healthcare Borrowing Costs

A. Baseline Analysis

We begin by testing the effects of smoke pollution on the borrowing costs of hospital and nursing home municipal bond issues relative to issues from other sectors in that county. The main dependent variable in this section is y_{ijt}, the offering yield spread for municipal issue i in county j and year-month t. The main independent variable is $Smoke_{jt}$, the annual population-weighted cumulative $PM_{2.5}$ exposure across census tracts within each county j for each year t. For ease of interpretation, this variable is normalized by subtracting its mean (145.5 $\mu g/m^3$) and then dividing the difference by its standard deviation (108.9 $\mu g/m^3$).

Formally, we test the following baseline OLS regression model:

$$y_{ijt} = \beta^H \cdot Smoke_{jt} \times Hospital_i + \beta^N \cdot Smoke_{jt} \times Nurse_i + \beta^C \cdot Smoke_{jt} + \gamma \cdot X_{ijt} + \delta \cdot Z_{it} + \phi_{ijy} + \varepsilon_{ijt}, \tag{1}$$

where *Hospital* and *Nurse* are indicator variables that equal one if the municipal bond issue is used to finance a hospital project and a nursing home project, respectively. The β^C coefficient measures the effect of *Smoke* on non-healthcare yield spreads, and the β^H and β^N coefficients measure the incremental effects of *Smoke* on hospital and nursing home yield spreads, respectively. The issue-level control variable vector X consists of the standalone *Hospital* and *Nurse* indicator variables, the natural logs of issue size and size-weighted number of years until maturity, indicator variables for whether the bond is callable, insured, general obligation, and issued in the negotiated market, and indicator variables for each credit rating and the unrated category.[2] The county-level control variable vector Z consists of the natural logs of median household income and median gross rent, the Hispanic and Black population shares, the housing vacancy rate, and the renter-to-owner occupancy ratio. The vector ϕ_{ijy} consists of state-year fixed effects and county fixed effects. Standard errors are clustered by county and year-month of issuance.

The results of this regression test are reported in Table III, column (1). We find that a one standard deviation increase in *Smoke* is associated with a 7.1 bps increase in the offering yield spread for hospitals, a 12.1 bps increase for nursing homes, and no change for non-healthcare issues. In column (2), we use industrial development bonds as our baseline

[2]Each of these indicator variables is also interacted with an indicator variable for each year of our sample period to account for time variation in the associated yield effects. The insured indicator variable, for example, is associated with lower municipal bond yields prior to the financial crisis but higher yields after the crisis (Bergstresser and Pontiff, 2013; Cornaggia, Hund and Nguyen, 2022).

instead of all non-healthcare bonds and find slightly stronger results (8.6 bps for hospitals and 13.3 bps for nursing homes). In columns (3) and (4), we use an alternative smoke measure (*SmokeDays*), calculated as the number of days in the year when wildfire smoke covered at least 75% of the census tracts in the county. (This variable is also normalized by subtracting its mean of 38.9 days and then dividing the difference by its standard deviation of 22.4 days.) For these tests, we find statistically significant point estimates that are similar to those in the first two columns.

The borrowing cost effects are highly economically significant. For hospitals, the 7.1 bps effect represents 11.9% of one standard deviation in the offering yield spread (59.9 bps), 7.7% of the credit spread between Aaa and Baa1 bonds (92.8 bps), and $175 million in additional present value interest costs on the $24.7 billion worth of hospital municipal bonds issued in above-mean *Smoke* counties. For these counties, the additional costs reverse the hospital yield savings from the US Affordable Care Act documented in Gao, Lee and Murphy (2022). For nursing homes, the 12.1 bps effect represents 20.2% of one standard deviation in the offering yield spread, 10.7% of the credit spread between Aaa and Baa1 bonds, and $95 million in additional present value interest costs on the $6 billion worth of nursing home municipal bonds issued in above-mean *Smoke* counties. Extrapolating forward, if the average annual exposure to wildfire smoke pollution were to increase again by 72 $\mu g/m^3$ over the next decade (66.1% of one standard deviation in our cumulative $PM_{2.5}$ exposure measure), then our point estimates suggest that repeat issues of hospital and nursing home municipal bonds from our main sample period would amount to another $585 million in out-of-sample present value interest costs.[3]

[3]The present value interest costs for in-sample and out-of-sample issues are calculated using the duration approximation formula, the point estimates of 7.1 bps for hospitals and 12.1 bps for nursing homes, and the average durations of 10 years for hospitals and 13 years for nursing homes.

Lastly, we estimate the per-patient total interest cost associated with wildfire smoke for future healthcare issues, where the *Smoke* shock is based on the decennial change in average $PM_{2.5}$ wildfire smoke exposure from Figure 4.[4] In Figure 5, we report the top ten counties with the highest per-patient total interest costs due to wildfire smoke, including Alameda County, CA, and Santa Rosa County, FL. We find that continued and heightened $PM_{2.5}$ wildfire smoke exposure can increase total present value interest costs by up to $250 per patient. This is a lower-bound estimate because wildfire smoke is expected to continue increasing over the next decade. These detrimental effects are consistent with reports in the popular press about sharp and continuous increases in the cost of care at hospitals and other healthcare facilities, particularly in California (AP News, 2022, 2024*a*).

B. *Out-of-State Wildfire Smoke*

State-level underinvestment in wildfire prevention can increase the amount of wildfire smoke in nearby states, thereby imposing costly externalities on the their healthcare systems. In this section, we analyze how drifting wildfire smoke plumes affect borrowing costs for healthcare providers in nearby states. Methodologically, we decompose our *Smoke* variable into its in-state and out-of-state components using 2010–2020 data on wildfires processed by St. Denis et al. (2023) and compiled by the US Department of Homeland Security National Incident Management System/Incident Command System (ICS). We model the *Smoke* process as follows:

$$Smoke_{jsy} = \beta \cdot F_{sy} \times \delta_s + \gamma \cdot F_{sy} + \delta_s + \varepsilon_{jsy}, \tag{2}$$

[4] For each county, we again apply the duration approximation formula to determine the total present value interest costs. The per-patient cost is the total present value interest cost divided by 10% of county population size, where 10% is the average number of patient admissions per capita (Kaiser Family Foundation, 2022).

where $F_{s,y}$ is a vector of in-state wildfire variables that includes the number of wildfires, the number of structures damaged, and the natural log of the number of burned acres in state s and year y.[5] To account for variation in state-level smoke predictability due to geographic factors such as weather, we interact the $F_{s,y}$ vector with state fixed effects (δ_s). The predicted component of wildfire smoke is attributable to in-state smoke ($HomeSmoke$), and the residual component is attributable to out-of-state smoke ($AwaySmoke$). For ease of interpretation, both variables are normalized by subtracting their respective means and then dividing the resulting differences by their respective standard deviations.

We re-test the baseline regression model in equation (1), except that we replace the $Smoke$ variable with its in-state and out-of-state components. The results are reported in column (1) of Table IV. We find that $HomeSmoke$ and $AwaySmoke$ both significantly increase borrowing costs for hospitals and nursing homes. Specifically, a one standard deviation increase in $HomeSmoke$ is associated with a 7.3 bps increase in hospital borrowing costs and a 14.6 bps increase in nursing home borrowing costs, and a one standard deviation increase in $AwaySmoke$ is associated with a 5.8 bps increase in hospital borrowing costs and a 9.2 bps increase in nursing home borrowing costs. In column (2), we re-test the same regression model in column (1), except that we use only industrial development bonds as our baseline instead of all non-healthcare bonds. In this case, we find slightly stronger results, but the takeaway remains the same, in that in-state and out-of-state wildfire smoke both significantly increase healthcare yields.

To better understand the economic implications of out-of-state wildfire smoke, consider an example of California and Nevada. In 2020, California experienced one of the most extreme wildfire years on record, with over four million acres burned by local wildfires. In

[5]To identify wildfire burn perimeters, we link the ICS data to the US Forest Service Monitoring Trends in Burn Severity database, which documents the spatial footprint of wildfires (Eidenshink et al., 2007).

the same year, out-of-state smoke in neighboring Nevada was about 2.5 standard deviations higher than its mean. Our point estimates in Table IV indicate that hospital borrowing costs would have increased by $5.8 \times 2.5 = 14.5$ bps as a result of the out-of-state smoke, while nursing home borrowing costs would have increased by $9.2 \times 2.5 = 23.0$ bps. For a hospital issue with an average size of \$90 million and duration of ten years, the out-of-state smoke effect would increase total present value interest costs by \$1.3 million. Similarly, for a nursing home issue with an average size of \$30 million and duration of 13 years, the out-of-state smoke effect would increase total present value interest costs by about \$0.9 million. Therefore, if Nevada were to build a hospital and a nursing home in 2020 and finance those investments using the municipal bond market, a high out-of-state smoke year, then wildfire smoke from California would increase the associated borrowing costs by \$2.2 million.

C. Prevention, Suppression, and Externalities

Should we classify the *AwaySmoke* effects as cross-state negative externalities or just spillovers? If a state underinvests in wildfire prevention and does not compensate healthcare providers in nearby states for the financial costs associated with drifting smoke plumes, then the "externality" classification is more appropriate. In this section, we provide a discussion of wildfire prevention efforts and suppression expenditures in California, where a large percentage of drifting wildfire smoke plumes currently originate in the US.

From a prevention perspective, related research supports the "externality" classification. In the case of California, the CCST notes that the state has a long history of underinvestment in wildfire prevention, and lacks a cost-benefit framework to evaluate prevention investments against suppression investments (Wara et al., 2020). A related Los Angeles Times article argues that this problem is largely institutional, in the sense that "institutional advancement for people [in the firefighting industry in California] has to do with how well you perform the firefighting mission, not how well you reduce firefighting hazard" (LA Times, 2020). The same article notes that the state also cancelled a $100 million pilot project to improve infrastructure resiliency to wildfires (the importance of which is underlined in Baylis and Boomhower, 2025), and about $155 million in funds previously earmarked for community protection and wildland fuel reduction. In combination with our findings, these results suggest that institutional and political frictions increase wildfire risk and impose costly externalities on nearby states.

Our supporting evidence suggests that California actually overinvests in wildfire suppression, perhaps as a consequence of its underinvestment in wildfire prevention. We collect available panel data on wildfire suppression expenditures from ten Western US state agencies that oversee wildfire suppression efforts (Cook and Becker, 2017). Using these data, we construct two outcome variables: state expenditure on wildfire suppression per burned acre (*StateExp/Acre*), and state-level federal expenditure on wildfire suppression per burned acre (*FedExp/Acre*). Our regression results in columns (1) and (2) of Table V indicate that California spends about $9,236 on wildfire suppression per burned acre, compared to an average of $680 per burned acre in the remaining states, even after controlling for the number of wildfires and the number of structures damaged in the state. We also find that the federal government pays California about $613 per burned acre for suppression efforts, compared to an average of $325 in the remaining states. Given the low investment in prevention and high investment in suppression, these results suggest states should establish a minimum threshold for prevention-to-suppression expenditures, similar to post-disaster spending requirements from FEMA (Wara et al., 2020).

D. Socially Vulnerable Populations

In the face of increasing wildfire risk, economists emphasize the importance of "scaling up cost-effective investments in physical protection and addressing disparities in protection and postfire recovery for socially vulnerable populations" (Boomhower, 2023; Baylis and Boomhower, 2025). In a similar vein, wildfire smoke pollution may also have a disproportionate effect on socially vulnerable populations (Banzhaf, Ma and Timmins, 2019), thereby imposing greater financial stress on local healthcare providers. In this section, we test the validity of this channel by exploiting cross-sectional variation in income levels and demographic characteristics.

We retest the baseline regression model in equation (1) using a stratified sampling approach based on poverty rate or minority share. First, we divide US counties into "high poverty" and "low poverty" subsamples using the median poverty rate of 16.7%.[6] The subsample regression results are reported in columns (1) and (2) of Table VI. We find that the *Smoke* effect on hospital yields is about 50% larger in high-poverty counties compared to low-poverty counties (8.4 bps versus 6.1 bps), and that the *Smoke* effect on nursing home yields is about twice as large in high-poverty counties (19.9 bps versus 9.9 bps). In columns (3) and (4), we divide US counties into "high minority" or "low minority" using the median combined share of Black and Hispanic residents (16.7%), and similarly find that the *Smoke* effects are larger in the high minority counties. Overall, our results suggest that wildfire smoke pollution also disproportionately affects vulnerable populations by placing greater financial stress on lower-income hospitals and nursing homes.

Related tests show that the borrowing cost effects are strongest for hospitals and nursing

[6]The poverty rate is calculated as the percentage of households in a county with a household income that is below the Federal Poverty Line, as defined annually by the Department of Health and Human Services. In 2024, for example, the Federal Poverty Line for a family of three, was $25,820.

homes that already have lower credit risk and thus less capacity to handle more patients with smoke-related illnesses. We divide our sample of healthcare issues into three groups: high quality (the top two credit rating categories), medium quality (the next two categories), and low quality (the remaining categories or unrated). Table VII reports the subsample regression results. We find the largest *Smoke* effects for low-quality hospitals (11.8 bps) and nursing homes (22.5 bps), a marginally statistically significant *Smoke* effect of 8.0 bps for medium-quality hospitals, and no effect for medium-quality nursing homes. For high-quality hospitals, we find a marginally statistically significant *Smoke* effect of -15.7 bps, suggesting an improvement in credit quality. One interpretation of this last finding is that hospitals with higher credit quality are more likely to receive patients with better insurance coverage.

E. Long-Run Beliefs about Wildfires

Wildfire smoke is more likely to be priced in the healthcare municipal bond market if investors believe that wildfires will remain a permanent part of the surrounding landscape. Otherwise, wildfire smoke is unlikely to be priced in this market if investors believe that the smoke is only temporary. Local investors are highly important for pricing municipal bonds because of tax advantages associated with holding local municipal bonds (Babina et al., 2021; Garrett et al., 2023), and thus their beliefs about future wildfire events likely determine the extent to which wildfire smoke is priced in the healthcare municipal bond market.

To explore this idea, we collect information on county-level beliefs on climate change, which has been shown to be correlated with wildfire risk perceptions (Lacroix, Gifford and Rush, 2019). In particular, we collect 2010–2019 survey data from the Yale Climate Opinions Maps website in order to determine the percentage of adults in the county that express worry about climate change, and the percentage of adults in the county that anticipate that global warming is personally harmful. This information is based on two key questions from the risk perceptions category of the survey: (1) How worried are you about global warming? (2) How much do you think global warming will harm you personally and people in the United States? We consider a county to be "high worry" or "low-worry" if the 2010–2019 average share of surveyed adults who answered "yes" to the first question is above-median or below-median, respectively. Similarly, we consider a county to be "high harm" or "low harm" if the 2010–2019 average share of surveyed adults who answered "yes" to the second question is above-median or below-median, respectively.

We re-test the baseline regression model in equation (1) using these four survey-based subsamples. Table VIII, column (1) indicates that a one standard deviation increase in *Smoke* in "high worry" counties is associated with a highly significant 7.9 bps increase in average offering yield spread for hospitals, and a 13.2 bps increase for nursing homes. For the "low worry" subsample in column (2), however, we find no statistically significant *Smoke* effects for hospitals or nursing homes. The results in columns (3) and (4) are similar, with highly significant *Smoke* point estimates in "high harm" counties, and no statistically significant point estimates in "low harm" counties. Overall, these results suggest that wildfire smoke is priced by local investors as long as they believe that climate change and the associated wildfires will persist in the long run. Conversely, in "low worry" and "low harm" counties, local investors are more likely to believe that wildfire smoke is temporary and thus not a public health or economic concern in the long run.[7]

[7]In terms of price efficiency, one interpretation of these results is that "low worry" investors may be transferring value to their local hospitals by ignoring the long-run impact of smoke pollution on hospital finances. Alternatively, "high worry" investors may be transferring value away from their local hospitals by overestimating the long-run impact of smoke pollution on hospital finances. Although the exact interpretation of wildfire risk perception falls outside the scope of our analysis, these results suggest that wildfire smoke is priced in the healthcare municipal bond market as long as local investors believe that wildfires will remain a permanent part of the landscape due to climate change.

V. Long-Term Migration and Residential Sorting

Smoke-induced migration patterns could potentially exacerbate the healthcare borrowing cost effects documented in the previous section. In a Rosen-Roback framework, which models the intercity equilibrium between wages and housing costs, increased exposure to smoke pollution acts as a negative amenity shock for local residents (Lopez and Tzur-Ilan, 2023; Chen, Oliva and Zhang, 2022). This shock motivates out-migration of high-skilled labor with relaxed mobility constraints (Rosen, 1979; Roback, 1982; Glaeser and Gyourko, 2005), but not necessarily out-migration of older or lower-income residents with tighter mobility constraints (US Census Bureau, 2024). The resulting patient mix could be highly unprofitable for healthcare service providers since older residents are more likely to be Medicare-insured and low-income residents are more likely to be uninsured or Medicaid-insured, thereby generating worse profit margins for hospital ER departments (Wilson and Cutler, 2014). In this section, we examine the long-run impact of smoke pollution exposure on the county population stock and county population flow.

A. Population Stock

Focusing on long-term residential sorting, we calculate the county-level percentage change in the population stock from 2009 to 2019 ($\%PopChange_{js}$) using population estimates from the ACS. We then test how $\%PopChange$ relates to county-level decennial changes in cumulative exposure to $PM_{2.5}$ wildfire smoke pollution ($SmokeChange$). In particular, we test the following OLS cross-sectional regression model:

$$\%PopChange_{js} = \beta \cdot SmokeChange_{js} + \delta_s + \varepsilon_{js}, \quad (3)$$

where δ_s represents state fixed effects, and $SmokeChange_{js}$ is calculated as the county-level average cumulative $PM_{2.5}$ wildfire smoke pollution exposure in 2016–2019 minus the county-level average in 2006–2009. This variable is also normalized by subtracting its mean and then dividing the difference by its standard deviation. Childs et al. (2022) apply a similar measure to describe systemic changes in exposure to smoke pollution.

The results are reported in column (1) of Table IX. We find that a one standard deviation increase in $SmokeChange$ is associated with a 0.68% decline in county-level population from 2009 to 2019, which is statistically significant at the 10% level. This supports the hypothesis that worsening air quality is associated with greater out-migration.

This migration behavior is not uniform across all age groups. We decompose $\%PopChange$ into two additive components: the change in population under 65 years of age as a percentage of county population in 2009, and the change in population at least 65 years of age as a percentage of county population in 2009, where 65 is the qualifying age for Medicare. Column (2) of Table IX shows that a one standard deviation increase in $SmokeChange$ is associated with a statistically significant 0.78% decrease in residents under 65 years of age, and column (3) shows that there is no statistically significant effect for residents aged 65 or older. These results suggest that the patient mix for hospitals skews more toward older residents in high-smoke areas and away from younger residents who would otherwise subsidize costly healthcare for older residents, further contributing to greater financial stress and higher credit risk for healthcare providers.

B. Population Flow

Skilled labor is correlated not only with age but also other individual characteristics such as credit score. In the next step of our migration analysis, we use the FRBNY Equifax

Consumer Credit Panel (CCP) data set to explore the effect of smoke pollution on residential sorting and county population flow in the cross-section of age and credit score. The CCP data set is a nationally representative sample of Equifax credit report data that contains a random, anonymous sample of 5% of US consumers with a credit file. The panel data allow us to observe if somebody has migrated from a particular county over an extended period.

Focusing on all households in the CCP data set as of the second quarter of 2010, we test the likelihood of county out-migration in response to long-term change in wildfire smoke pollution using the following linear probability model:

$$OutMigration_{ij} = \beta \cdot SmokeChange_{js} + \gamma \cdot X_i + \delta_s + \varepsilon_{js}. \tag{4}$$

In this specification, $OutMigration_i$ is an indicator variable that equals 1 if individual i moves out of county j by 2019, X_i is a vector of individual characteristics that includes age and Equifax Risk Score (a measure of credit score by Equifax) in 2010, and δ_s is a vector of state fixed effects.

We test the above regression model for subsamples of individuals based on different combinations of age and Equifax Risk Score. In terms of age, we focus on individuals aged 20-40 (1.8 million observations), 40-65 (4.5 million observations), and 65-85 (2.5 million observations). In terms of Equifax Risk Score, we focus on individuals with an Equifax Risk Score below 620 (subprime borrowers; 1.8 million observations), between 620-660 (near-prime borrowers; 0.7 million observations), between 660-720 (prime borrowers; 1.2 million observations), between 720-780 (super-prime borrowers; 1.7 million observations), and above 780 (super-prime-plus borrowers; 3.4 million observations). Altogether, we test 15 subsample regressions based on the three age groups and five Equifax Risk Score groups.

The resulting point estimates on $SmokeChange$ for these subsample regressions are reported numerically in Table X and graphically in Figure 6. We find that the strongest smoke effect on out-migration is concentrated among individuals aged 20-40 that are in the highest Equifax Risk Score group. For these individuals, a one standard deviation increase in $SmokeChange$ is associated with a statistically significant 2.2% increase in out-migration over ten years. Statistically significant effects are also observed for individuals aged 40-65 that are in the highest or second-highest Equifax Risk Score groups (1.1% and 1.0%, respectively). These results indicate that wildfire smoke is more likely to drive away younger, productive residents with strong credit scores, thereby skewing the patient composition toward the remaining age and credit score groups. Given that many older residents are Medicare-insured and many low-credit residents are uninsured or Medicaid-insured, hospitals in high-smoke areas are exposed to greater operational challenges through the migration channel in the long run.

VI. Real Investment Effects

In this last section, we analyze the effect of wildfire smoke pollution on real investment spending for hospitals. If wildfire smoke strains hospital financial resources and increases their cost of capital, then hospitals may respond by reducing average investment activity and relying more on endowment returns to generate investment capital. On the latter point, Q-theory predicts that investment spending should only respond to cash flow shocks in the presence of market frictions—in practice, the two most relevant frictions being agency conflicts and financial constraints (Stein, 2003). In the non-profit hospital setting, Adelino, Lewellen and Sundaram (2015) provides strong evidence that investment sensitivity to cash flow shocks is attributable only to the latter, likely due to the unique governance structure of non-profit hospitals. Therefore, higher investment sensitivity to cash flow shocks can be interpreted as tighter financial constraint in this context.

Adapting the methodology from Adelino, Lewellen and Sundaram (2015), we use hospital financial variables from the HCRIS database to test the effects of wildfire smoke pollution on non-profit hospital investment spending and financial constraints. The main dependent variables used in this section are the future one-year and two-year growth rates in net fixed assets for each hospital h in county j and year t: $g(NFA)_{h,j,t+1}$ and $g(NFA)_{h,j,t+2}$. The main independent variables are (1) our central wildfire smoke pollution measure, $Smoke_{j,t}$, (2) the ratio of hospital endowment fund investment income in year t to net fixed assets in year $t-1$ ($InvInc_{h,j,t}$), which is meant to capture cash flow shocks that are uncorrelated with the investment opportunity set (Bakke and Whited, 2012), and (3) the interaction of these two variables, $InvInc_{h,j,t} \times Smoke_{j,t}$. In a standard OLS regression that uses these variables as inputs, the point estimate on $Smoke_{j,t}$ captures the direct effect of wildfire smoke pollution on investment spending, while the point estimate on $InvInc_{h,i,t} \times Smoke_{j,t}$ captures hospital financial constraints that are attributable to wildfire smoke pollution.

Formally, we test the following OLS regression model:

$$\begin{aligned} g(NFA)_{h,j,t+k} &= \beta_1 \cdot Smoke_{j,t} + \beta_2 \cdot InvInc_{h,j,t} + \beta_3 \cdot InvInc_{h,j,t} \times Smoke_{j,t} \\ &+ \delta \cdot X_{h,j,t} + \varepsilon_{h,j,t}, \end{aligned} \quad (5)$$

where $k \in \{1, 2\}$. The control variable vector $X_{h,j,t}$ from Adelino, Lewellen and Sundaram (2015) includes the following: $g(SRev)$, the percentage change in hospital net service revenue from $t-1$ to t; $OpInc$, the ratio of operating income in year t to net fixed assets in year

$t-1$; $\log(TRev)$, the natural log of total revenue in year t; $FinInv$, the ratio of financial investment value to net fixed assets for the hospital in year $t-1$; and state-year and hospital fixed effects. As in Adelino, Lewellen and Sundaram (2015), we require each hospital to have at least \$1 million in assets and service revenue, and truncate each variable at the top 1% and bottom 1% of its distribution. The summary statistics in Table XI indicate that the distributions of these variables are fairly similar to what is reported in Adelino, Lewellen and Sundaram (2015).

The regression results are reported in Table XII. We start with two-year net fixed asset growth because Adelino, Lewellen and Sundaram (2015) find that investment-cash flow sensitivities are strongest over a two-year horizon, as hospital investments are highly capital intensive and take more time to implement. The results in column (1) indicate that a one standard deviation increase in $InvInc$ (0.042) is associated with a 2.6 percentage point increase (0.619×0.042) in two-year fixed asset growth, or 7.2% of one standard deviation in two-year fixed asset growth. Importantly, the positive and statistically significant point estimate on $Smoke \times InvInc$ (0.278) indicates that the responsiveness of two-year fixed asset growth to investment income increases by 45% when the $Smoke$ variable is one standard deviation larger. The negative point estimate on the standalone $Smoke$ variable indicates that wildfire smoke also directly reduces two-year fixed asset growth by 2.3 percentage points, although the statistical significance is weaker in this case. In column (2), we also add the county-level control variables from our baseline tests, and find similar results. In columns (3) and (4), we re-test the same regressions using one-year fixed asset growth. Consistent with Adelino, Lewellen and Sundaram (2015), we find only marginally significant investment-cash flow sensitivity effects in this case. Overall, the evidence from these tests indicates that wildfire smoke exacerbates financial constraints and reduces investment activity over longer horizons.

Lastly, in Internet Appendix A, we provide supporting evidence that wildfire smoke is associated with an increase in respiratory illnesses and ER visits. In particular, we show that a one standard deviation in *Smoke* is associated with 8.8 additional asthma cases per 1,000 people and 2.4 additional ER visits per 1,000 people. Furthermore, we show that *AwaySmoke* is also associated with more asthma cases and ER visits. Given that wildfire smoke pollution disproportionately affects older households and lower-income households, and evidence that ER profit margins from these groups are highly negative (Wilson and Cutler, 2014), our results suggest that wildfire smoke reduces profit margins for hospitals, thereby increasing their credit risk.

VII. Conclusion

Large-scale wildfires have become increasingly common over the last several decades, and the physical damages to areas in the associated burn regions are unprecedented. Municipalities that are downwind of wildfires do not suffer from physical damages but do suffer the health and economic costs of poor air quality, even when the origin of the fire is in another state or country. In many regions, these costs are expected to increase as air quality deteriorates—for example, according to a 2024 report by First Street, the number of poor air quality days in some areas of California is expected to increase from 60 days to over 90 days in the next 30 years.

We estimate financial costs of wildfire smoke by leveraging variation in a novel measure of wildfire smoke exposure that is exogenous to the local economy. We show that exposure to wildfire smoke is associated with significantly higher borrowing costs for hospitals and nursing homes. Specifically, a one standard deviation increase in smoke pollution exposure is associated with a 7.1 bps increase in offering yield spread for hospital issues, and a 12.1 bps increase for nursing home issues. In high-smoke counties, these effects translate to about $175 million in realized interest costs for hospital issues and $95 million for nursing home issues. Importantly, we find that out-of-state wildfire smoke is a significant contributor to these borrowing costs effects, suggesting that poor wildfire management imposes costly externalities on other states. Indeed, we find evidence that California, a major source of drifting wildfire smoke for many states in recent years, underinvests in wildfire prevention and consequently overinvests in wildfire suppression.

Although the focus of this paper is on wildfire smoke pollution, our results provide guidance on cost externalities from other pollution sources. For example, crop burning in rural regions of India during the fall months significantly increases hazardous smoke pollution in nearby cities, resulting in an alarming increase in respiratory illnesses and deaths (IQAir, 2024). Healthcare-uninsured rates are extremely high in India, and these smoke-related illnesses are likely to translate to significant financial stresses for local hospitals. The smoke elasticities documented in this paper can be used to quantify the financial effects of crop pollution on nearby hospitals, thereby providing guidance on how to impose penalties for illegal crop burning or compensate local farmers to reduce crop burning.

The costs associated with preventing and suppressing wildfires are steadily increasing, and intergovernmental cooperation is crucial for addressing wildfire events. Our evidence suggests that policymakers should account for the costly externalities that wildfires impose on other states when determining how to optimally split the associated prevention and suppression costs. A key question policymakers should be asking is who is best suited to determine how much to spend on wildfire mitigation, especially in light of these externalities.

For within-state smoke, if adjacent local governments are unable to negotiate on how to split the associated costs, then the state government may be able to step in and determine an optimal solution. For smoke that travels across state borders, the federal government and the EPA may be more effective in coordinating efforts to mitigate wildfire risk and minimize the costly externalities documented in this study.

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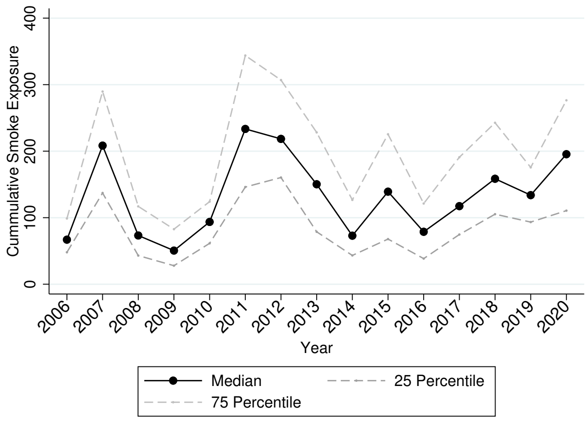
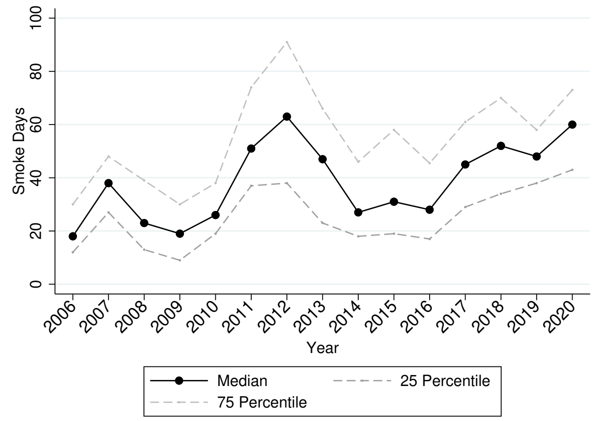


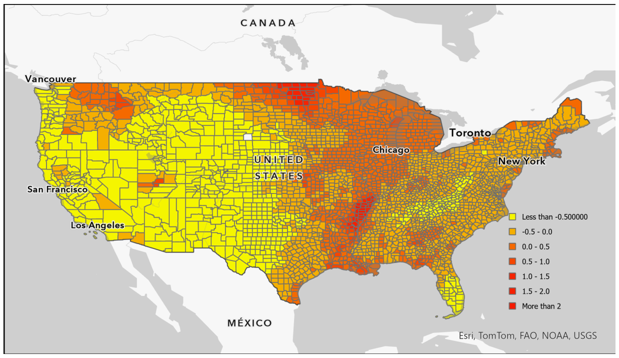
(a) Smoke Exposure



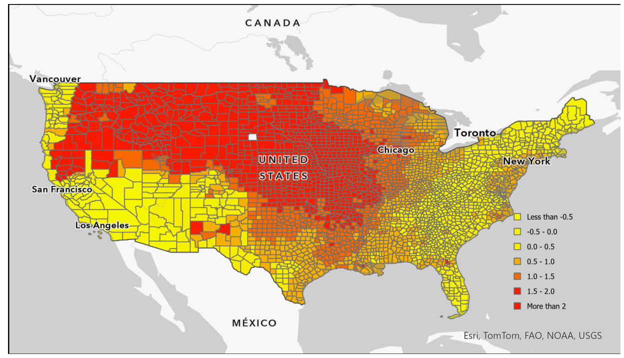
(b) Smoke Days

Figure 1. U.S. Wildfire Smoke by Year

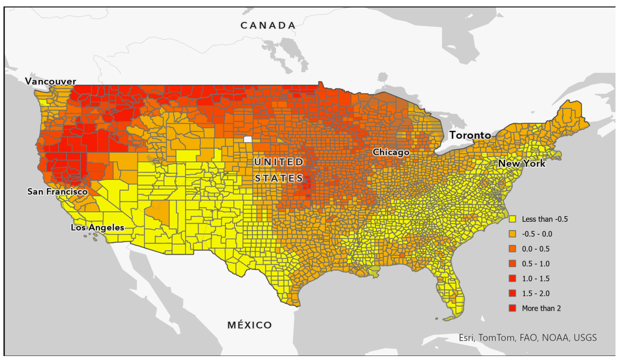
This figures provides time-series statistics on county-level cumulative wildfire smoke exposure and number of smoke days from 2006 to 2020. Annual cumulative wildfire smoke exposure for each county is population-weighted at the census tract-level. A smoke day occurs when more than 75% of the census tracts in a county have a non-zero ground-level reading of $PM_{2.5}$ wildfire smoke. The $PM_{2.5}$ wildfire smoke data are obtained from the Stanford Echo Lab (Childs et al., 2022).



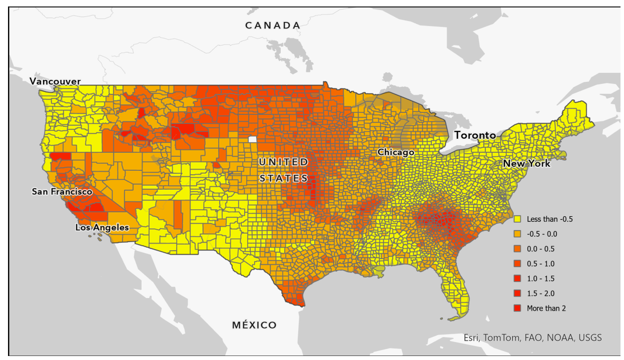
(a) 2010



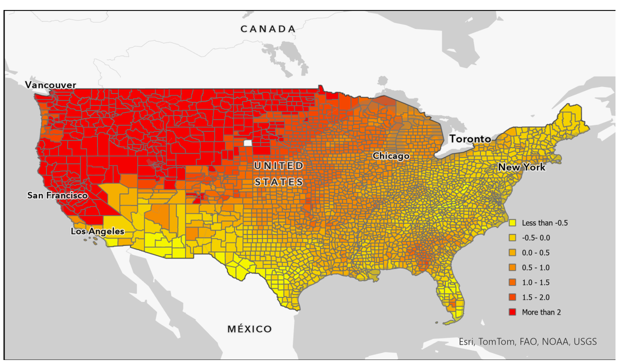
(b) 2012



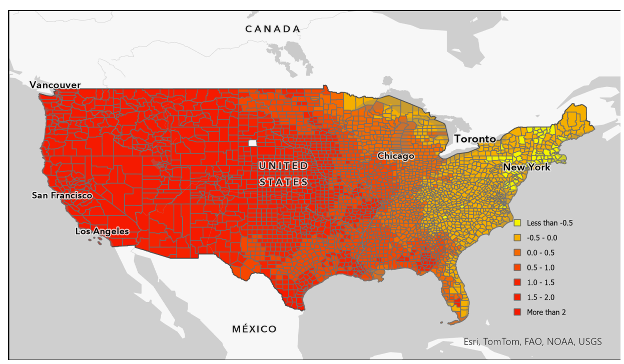
(c) 2014



(d) 2016



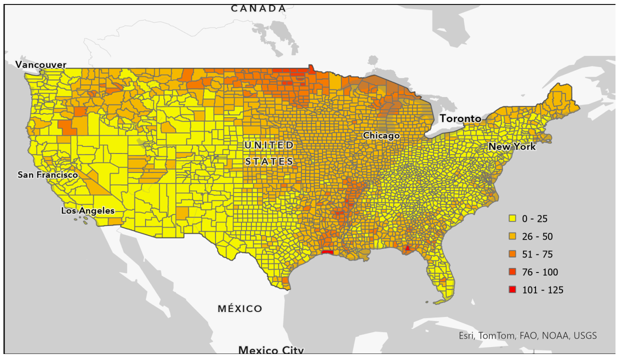
(e) 2018



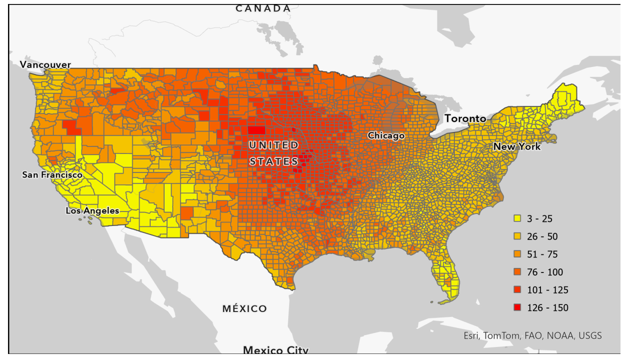
(f) 2020

Figure 2. U.S. Wildfire Smoke Exposure

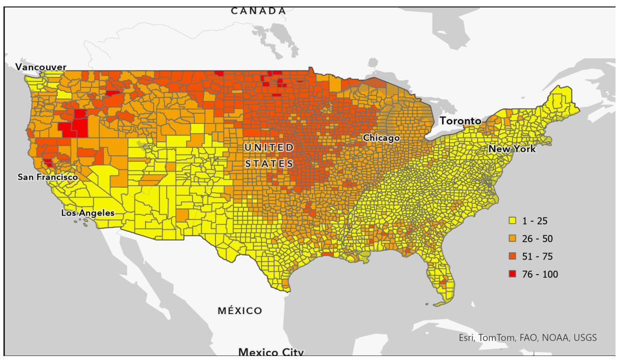
This figure provides heat maps of wildfire smoke intensity for each even year from 2010 to 2020. Wildfire smoke intensity is the standardized population-weighted cumulative amount of smoke $PM_{2.5}$ exposure during the county-year across census tracts, where the standardization is based on the mean and standard deviation in 2006–2009. Counties (and areas) with missing population data or smoke pollution data are blank. The $PM_{2.5}$ wildfire smoke data are obtained from the Stanford Echo Lab (Childs et al., 2022).



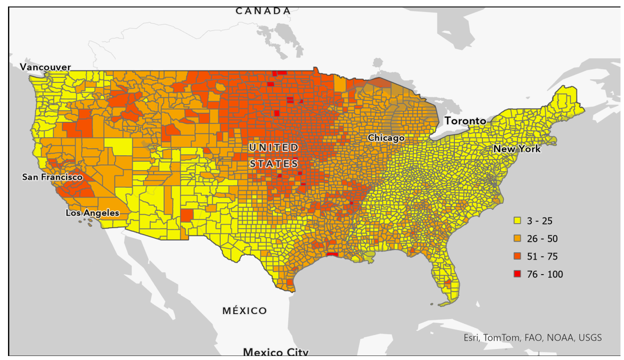
(a) 2010



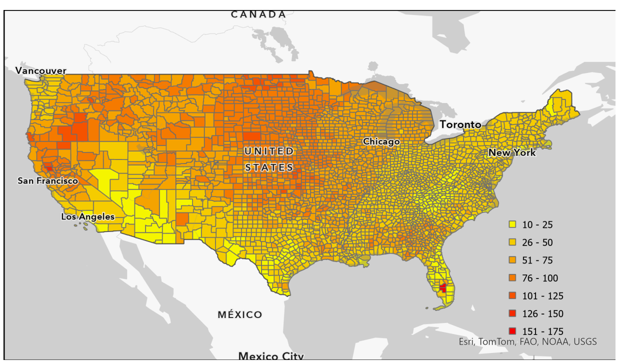
(b) 2012



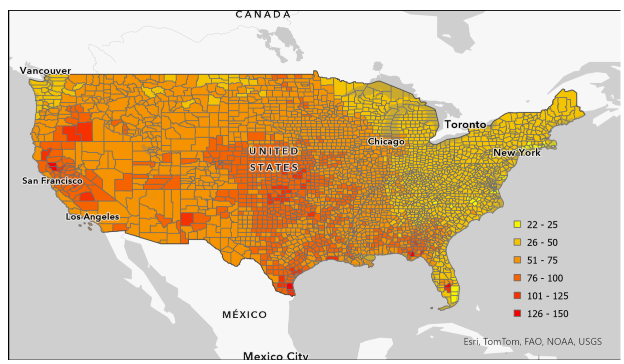
(c) 2014



(d) 2016



(e) 2018



(f) 2020

Figure 3. U.S. Wildfire Smoke Days

This figure provides heat maps of county-level smoke days for each even year from 2010 to 2020. A smoke day occurs when more than 75% of the census tracts in a county have a non-zero ground-level reading of $PM_{2.5}$ wildfire smoke. The $PM_{2.5}$ wildfire smoke data are obtained from the Stanford Echo Lab (Childs et al., 2022).

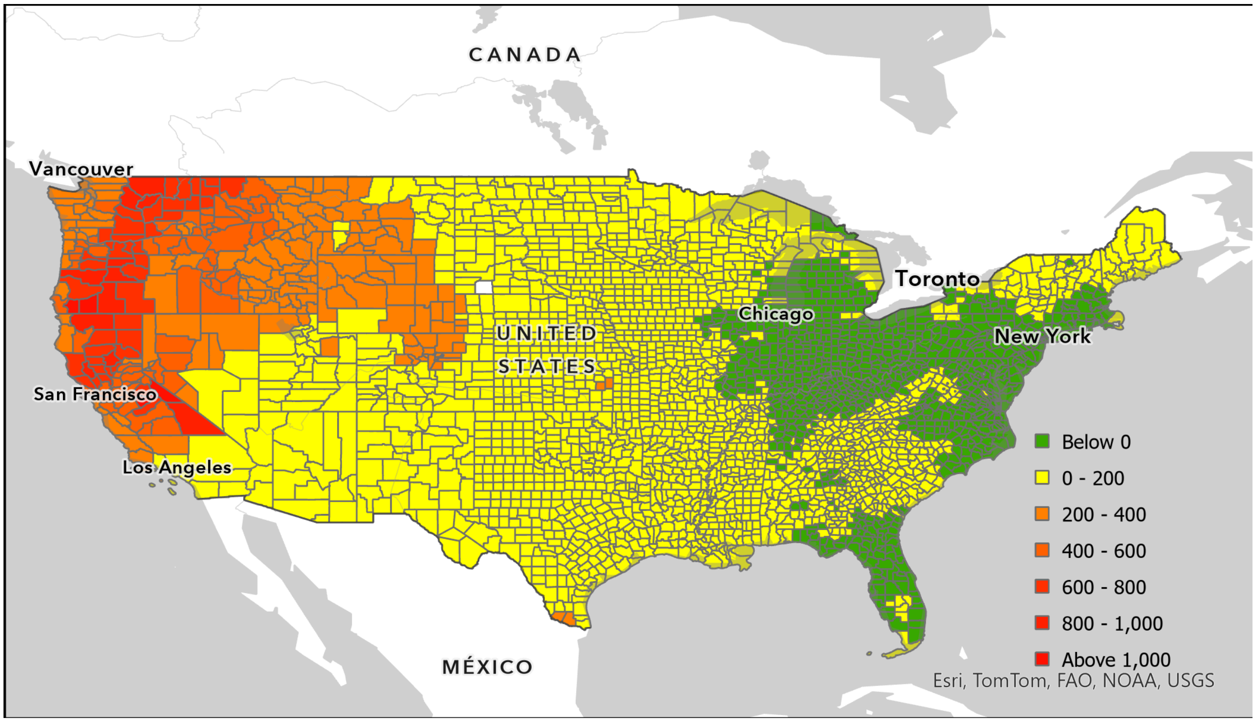


Figure 4. Decennial Change in Annual Cumulative Smoke Exposure

This figure provides a heat map of the decennial change in cumulative $PM_{2.5}$ wildfire smoke exposure. Decennial change is calculated as the county-level average cumulative $PM_{2.5}$ wildfire smoke exposure in 2016–2020 minus the county-level average in 2006–2010. The $\mathrm{PM}_{2.5}$ wildfire smoke data are obtained from the Stanford Echo Lab (Childs et al., 2022).

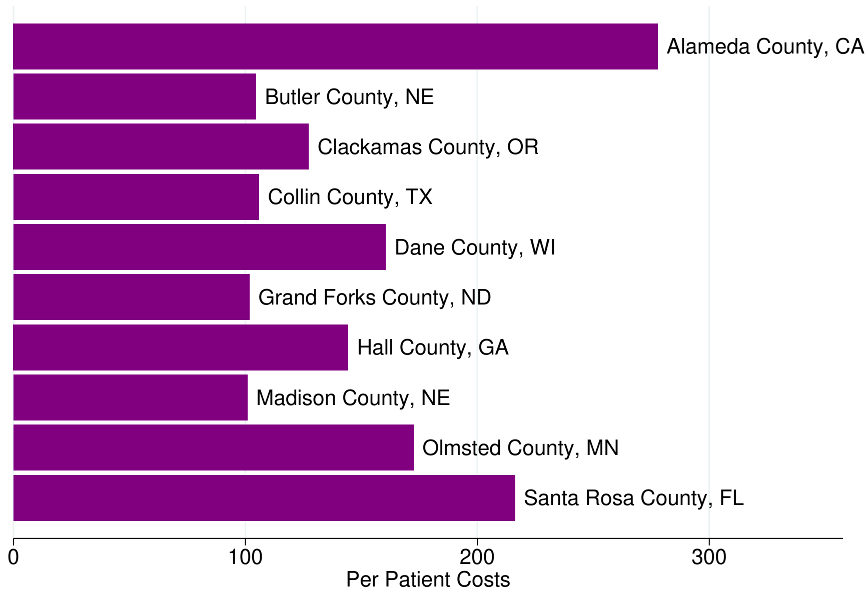


Figure 5. Top Ten Counties by Future Wildfire Pollution Borrowing Costs

This bar graph reports the estimated smoke-induced future interest cost per patient for out-of-sample healthcare issues. Estimates are reported for the ten counties that experienced the largest projected costs based on (1) the decennial change in wildfire smoke pollution reported in Figure 4, (2) total healthcare issue size, (3) the average duration, and (4) 10% of the county population size, as 10% is approximately the average number of patient admissions per capita.

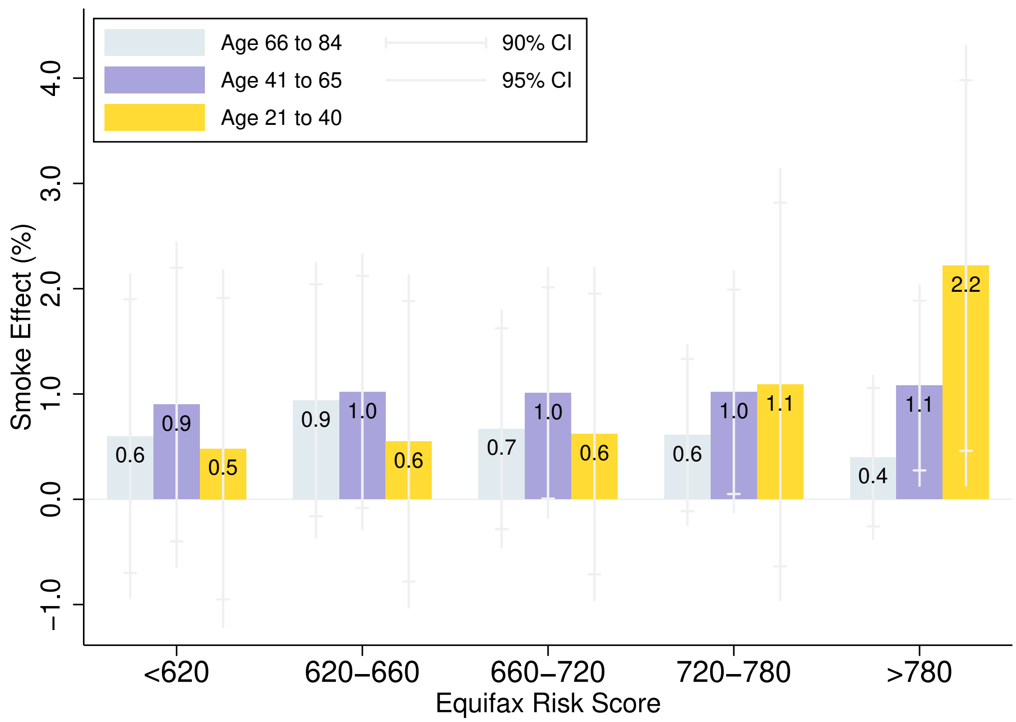


Figure 6. The Effects of Smoke Pollution on Out-Migration by Age and Credit Score

This figure reports linear probability model estimates of the effects of wildfire smoke pollution on out-migration for different subgroups based on information from the FRBNY Consumer Credit Panel (CCP)/Equifax data set. The dependent variable is $OutMigration$, an indicator variable that equals 1 if the individual in 2010 moved to a different county by 2019. The main independent variable is $SmokeChange$, calculated as average population-weighted cumulative smoke exposure in 2016–2019 minus its value in 2006–2009. $SmokeChange$ is standardized by subtracting its mean and then dividing the difference by its standard deviation. Each bar reports the point estimate of $SmokeChange$ for a different subsample regression based on a combination of age group and Equifax Risk Score group. The gray vertical line for each bar represents the 95% confidence interval for the associated point estimate.

Table I: Municipal Bond Summary Statistics by Sector

Panel A: Non-Healthcare	Mean	Median	P25	P75	SD
Offering Yield Spread (%)	0.316	0.229	-0.021	0.557	0.578
Issue Size (M)	22.164	7.000	3.000	16.500	66.054
Years to Maturity	7.870	7.848	4.786	10.497	4.808
Rating Number	18.423	19.000	17.000	20.000	1.859
Unrated	0.265	0.000	0.000	1.000	0.441
General Obligation	0.673	1.000	0.000	1.000	0.469
Insured	0.145	0.000	0.000	0.000	0.352
Callable	0.714	1.000	0.000	1.000	0.452
Negotiated	0.301	0.000	0.000	1.000	0.459
Observations	76,075				

Panel B: Hospitals	Mean	Median	P25	P75	SD
Offering Yield Spread (%)	0.977	0.890	0.495	1.404	0.758
Issue Size (M)	90.559	35.148	8.777	106.520	177.646
Years to Maturity	11.281	10.323	7.698	12.916	6.564
Rating Number	16.224	16.000	15.000	18.000	2.336
Unrated	0.247	0.000	0.000	0.000	0.432
General Obligation	0.176	0.000	0.000	0.000	0.381
Insured	0.042	0.000	0.000	0.000	0.200
Callable	0.892	1.000	1.000	1.000	0.310
Negotiated	0.735	1.000	0.000	1.000	0.442
Observations	1,060				

Panel C: Nursing Homes	Mean	Median	P25	P75	SD
Offering Yield Spread (%)	1.675	1.737	0.956	2.353	0.986
Issue Size (M)	31.611	21.007	6.945	40.455	37.569
Years to Maturity	16.058	13.466	9.268	22.095	8.859
Rating Number	14.650	14.000	12.000	17.000	3.086
Unrated	0.647	1.000	0.000	1.000	0.478
General Obligation	0.068	0.000	0.000	0.000	0.253
Insured	0.014	0.000	0.000	0.000	0.116
Callable	0.969	1.000	1.000	1.000	0.173
Negotiated	0.791	1.000	1.000	1.000	0.407
Observations	584				

This table reports summary statistics for non-healthcare municipal bond issues (Panel A), hospital municipal bond issues (Panel B), and nursing home municipal bond issues (Panel C) from 2010 to 2019.

Table II: Wildfire Smoke Pollution Summary Statistics

	Cumulative Smoke Exposure		Annual Smoke Days	
	(1) Mean	(2) SD	(3) Mean	(4) SD
2006	80.530	57.282	22.603	13.098
2007	223.566	138.171	38.583	15.671
2008	95.396	122.342	27.443	16.921
2009	60.500	41.738	20.725	13.695
2010	93.697	48.907	28.929	14.065
2011	251.727	140.227	54.741	25.498
2012	247.091	154.717	65.507	29.530
2013	158.325	106.096	44.989	22.520
2014	91.013	67.269	31.339	17.115
2015	173.958	158.386	38.314	23.090
2016	87.907	59.499	32.095	17.709
2017	184.599	240.326	46.064	19.485
2018	217.097	231.350	52.877	21.281
2019	140.465	64.905	48.401	15.492
2020	281.228	387.816	58.846	19.719
Decennial Change	71.522	139.437	20.000	8.236

Columns (1) and (2) report the mean and standard deviation of cumulative population-weighted smoke pollution ($PM_{2.5}$) exposure per year, respectively. Columns (3) and (4) report the mean and standard deviation of the number of days when wildfire smoke is present ($PM_{2.5} > 0$) for at least 75% of the census tracts per year, respectively. Decennial Change is calculated as the average in 2016–2020 minus the average in 2006–2010.

Table III: Wildfire Smoke Pollution and Healthcare Offering Yield Spreads (%)

	(1) Yield Spread (%)	(2) Yield Spread (%)	(3) Yield Spread (%)	(4) Yield Spread (%)
$Smoke \times Hospital$	0.071***	0.086***		
	(0.021)	(0.020)		
$Smoke \times Nurse$	0.121***	0.133***		
	(0.040)	(0.034)		
$Smoke$	0.008	0.001		
	(0.006)	(0.008)		
$SmokeDays \times Hospital$			0.061***	0.093***
			(0.021)	(0.023)
$SmokeDays \times Nurse$			0.078**	0.113***
			(0.033)	(0.034)
$SmokeDays$			0.018*	0.014
			(0.010)	(0.015)
Controls	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Rating-Year FE	Yes	Yes	Yes	Yes
Insured-Year FE	Yes	Yes	Yes	Yes
Callable-Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Baseline	Non-HN	Ind. Dev.	Non-HN	Ind. Dev.
Adj. R^2	0.581	0.646	0.581	0.646
N	76,863	28,596	76,863	28,596

This table reports ordinary least squares estimates of the effects of smoke pollution on municipal borrowing costs. The dependent variable is offering yield spread (%), and the main independent variables are *Smoke* and *SmokeDays*, both of which are interacted with the *Hospital* and *Nurse* indicator variables. *Smoke* is the population-weighted cumulative amount of smoke $PM_{2.5}$ exposure during the county-year. *SmokeDays* is the number of days when wildfire smoke covered at least 75% of the census tracts in the county-year. Both smoke variables are standardized by subtracting their means and then dividing the differences by their respective standard deviations. The odd columns use all non-healthcare bonds as the baseline group, and the even columns use only industrial development bonds as the baseline group. The control variables are specified in the main text. Robust standard errors clustered by county and issuance year-month are reported in parentheses. The stars *, **, ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table IV: In-State and Out-of-State Smoke Effects on Healthcare Yield Spreads

	(1) Yield Spread (%)	(2) Yield Spread (%)
$HomeSmoke \times Hospital$	0.073**	0.095***
	(0.028)	(0.023)
$HomeSmoke \times Nurse$	0.146**	0.150***
	(0.057)	(0.052)
$AwaySmoke \times Hospital$	0.058**	0.059**
	(0.024)	(0.023)
$AwaySmoke \times Nurse$	0.092*	0.097**
	(0.053)	(0.044)
$AwaySmoke$	0.006	-0.002
	(0.005)	(0.009)
Controls	Yes	Yes
State-Year FE	Yes	Yes
Rating-Year FE	Yes	Yes
Insured-Year FE	Yes	Yes
Callable-Year FE	Yes	Yes
County FE	Yes	Yes
Baseline	Non-HN	Ind. Dev.
Adj. R^2	0.576	0.649
N	65,343	23,046

This table reports ordinary least squares estimates of the effects of in-state and out-of-state smoke pollution on municipal borrowing costs. The dependent variable is offering yield spread (%), and the main independent variables are *HomeSmoke* and *AwaySmoke*, both of which are interacted with the $Hospital$ and $Nurse$ indicator variables. *Smoke* is the standardized population-weighted cumulative amount of smoke $PM_{2.5}$ exposure during the county-year. $HomeSmoke$ is the predicted component of *Smoke* based on a regression of *Smoke* on wildfire data specified in the text, and *AwaySmoke* is the residual component from that regression. $HomeSmoke$ and *AwaySmoke* are standardized by subtracting their means and then dividing the differences by their respective standard deviations. Column (1) uses all non-healthcare bonds as the baseline group, and column (2) uses only industrial development bonds as the baseline group. The control variables are specified in the main text. Robust standard errors clustered by county and issuance year-month are reported in parentheses. The stars *, **, ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table V: Fire Suppression Expenditures

	(1) StateExp/Acre	(2) StateExp/Acre	(3) FedExp/Acre	(4) FedExp/Acre
$\mathbf{1}_{CA}$	8555.68***	30106.22***	287.86*	1514.87***
	(2380.79)	(7428.03)	(155.31)	(376.57)
N(Fires)		-121.66***		-7.89***
		(38.09)		(2.50)
$\mathbf{1}_{CA} \times N$(Fires)		-0.61		0.82
		(2.08)		(1.75)
N(Str. Damaged)		-3.87**		0.80
		(1.65)		(0.49)
$\mathbf{1}_{CA} \times N$(Str. Dmg.)		-1.55**		-1.01**
		(0.64)		(0.48)
Constant	679.98***	764.79***	324.67***	296.17***
	(130.06)	(205.55)	(78.83)	(110.90)
Adj. R^2	0.494	0.773	0.010	0.008
N	85	85	81	81

This table reports results of OLS regressions that use annual state expenditure per burned acre (columns (1) and (2)) or state-specific federal expenditure per burned acre as the dependent variable (columns (3) and (4)). The independent variables used in these regressions are an indicator variable for California ($\mathbf{1}_{CA}$), the state-year number of wildfires, the state-year number of structures damaged by wildfires, and the interactions of these latter two variables with $\mathbf{1}_{CA}$. Robust standard errors are reported in parentheses. The stars *, **, ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table VI: Wildfire Smoke Pollution Effects by Demographics

	(1) Yield Spread (%)	(2) Yield Spread (%)	(3) Yield Spread (%)	(4) Yield Spread (%)
Smoke × *Hospital*	0.084***	0.061*	0.071***	0.046
	(0.026)	(0.033)	(0.025)	(0.034)
Smoke × *Nurse*	0.199**	0.099**	0.253***	0.124**
	(0.086)	(0.050)	(0.069)	(0.059)
Smoke	-0.002	0.005	0.010	0.002
	(0.009)	(0.005)	(0.008)	(0.008)
Controls	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Rating-Year FE	Yes	Yes	Yes	Yes
Insured-Year FE	Yes	Yes	Yes	Yes
Callable-Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Subsample	High Poverty	Low Poverty	High Minority	Low Minority
Adj. R^2	0.567	0.579	0.613	0.557
N	34,235	42,138	41,356	35,430

This table reports ordinary least squares estimates of the effects of smoke pollution on municipal borrowing costs for different demographic subsamples. The dependent variable is offering yield spread (%), and the main independent variables are *Smoke* and *SmokeDays*, both of which are interacted with the *Hospital* and *Nurse* indicator variables. *Smoke* is the standardized population-weighted cumulative amount of smoke $PM_{2.5}$ exposure during the county-year. In columns (1) and (2), we use subsamples of counties with above-median and below-median poverty, respectively. In columns (3) and (4), we use subsamples of counties with above-median and below-median minority share, respectively. The control variables are specified in the main text. Robust standard errors clustered by county and issuance year-month are reported in parentheses. The stars *, **, ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table VII: Wildfire Smoke Pollution Effects by Bond Quality

	(1) Yield Spread (%)	(2) Yield Spread (%)	(3) Yield Spread (%)
Smoke × *Hospital*	-0.157*	0.080*	0.118***
	(0.085)	(0.043)	(0.024)
Smoke × *Nurse*	-0.096	0.000	0.225***
	(0.092)	(0.089)	(0.044)
Smoke	-0.001	0.001	0.018*
	(0.009)	(0.006)	(0.010)
Controls	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes
Rating-Year FE	Yes	Yes	Yes
Insured-Year FE	Yes	Yes	Yes
Callable-Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Rating Subsample	High	Medium	Low/Unrated
Adj. R^2	0.398	0.497	0.632
N	15,427	25,807	34,777

This table reports ordinary least squares estimates of the effects of smoke pollution on municipal borrowing costs for different bond quality subsamples. The dependent variable is offering yield spread (%), and the main independent variables are *Smoke* and *SmokeDays*, both of which are interacted with the *Hospital* and *Nurse* indicator variables. *Smoke* is the standardized population-weighted cumulative amount of smoke $PM_{2.5}$ exposure during the county-year. The subsamples used columns (1), (2), and (3) are comparised of bonds with high credit quality (top two ratings categories), medium credit quality (next two ratings categories), and low/unrated credit quality (remaining credit ratings or no credit rating). The control variables are specified in the main text. Robust standard errors clustered by county and issuance year-month are reported in parentheses. The stars *, **, ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table VIII: Wildfire Smoke Pollution Effects by Climate Change Beliefs

	(1) Yield Spread (%)	(2) Yield Spread (%)	(3) Yield Spread (%)	(4) Yield Spread (%)
Smoke × *Hospital*	0.079***	0.044	0.083***	0.036
	(0.021)	(0.048)	(0.021)	(0.050)
Smoke × *Nurse*	0.132***	0.016	0.123**	0.056
	(0.047)	(0.087)	(0.051)	(0.071)
Smoke	0.006	-0.004	0.006	0.013
	(0.006)	(0.010)	(0.006)	(0.012)
Controls	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Rating-Year FE	Yes	Yes	Yes	Yes
Insured-Year FE	Yes	Yes	Yes	Yes
Callable-Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Subsample	High Worry	Low Worry	High Harm	Low Harm
Adj. R^2	0.602	0.513	0.604	0.513
N	61,017	15,802	59,374	17,444

This table reports ordinary least squares estimates of the effects of smoke pollution on municipal borrowing costs for different climate change belief subsamples. The dependent variable is offering yield spread (%), and the main independent variables are *Smoke* and *SmokeDays*, both of which are interacted with the *Hospital* and *Nurse* indicator variables. *Smoke* is the standardized population-weighted cumulative amount of smoke $PM_{2.5}$ exposure during the county-year. The subsamples used columns (1) and (2) are comprised of counties with above-median and below-median worry about climate change, respectively. The subsamples used in columns (3) and (4) are comprised of counties with above-median and below-median concern that climate change will be at least moderately harmful to US residents, respectively. The control variables are specified in the main text. Robust standard errors clustered by county and issuance year-month are reported in parentheses. The stars *, **, ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table IX: The Effects of Smoke Pollution on Municipal Population

	(1) $\%PopChange$	(2) $\%PopChange < 65$	(3) $\%PopChange \geq 65$
$SmokeChange$	-0.684*	-0.775**	0.091
	(0.390)	(0.382)	(0.168)
State FE	Yes	Yes	Yes
Adj. R^2	0.140	0.121	0.177
N	3,106	3,106	3,106

This table reports ordinary least squares estimates of the effect of smoke pollution on migration. The dependent variables in columns (1), (2), and (3) are the 2009–2019 county-level percentage change in total population, the 2009–2019 county-level change in population aged under 65 as a percentage of population in 2009, and the 2009–2019 county-level change in population aged 65 or older as a percentage of population in 2009. $SmokeChange$ is calculated as average population-weighted cumulative smoke exposure in 2016–2019 minus average population-weighted cumulative smoke exposure in 2006–2009. $SmokeChange$ is standardized by subtracting its mean and then dividing the difference by its standard deviation. Robust standard errors clustered by state are reported in parentheses. The stars *, **, ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively. Source: U.S. Census Bureau American Community Survey and Echo Stanford Lab.

Table X: The Effects of Smoke Pollution on Out-Migration by Age and Credit Score

Equifax Risk Score	(1) Age Below 40	(2) Age 40-65	(3) Age Above 65
Below 620	0.005	0.009	0.006
620-660	0.005	0.010	0.009
660-720	0.006	0.010	0.007
720-780	0.011	0.010*	0.006
Above 780	0.022**	0.011**	0.004

This table reports 15 separate linear probability model estimates of the effect of wildfire smoke pollution on out-migration. Each subgroup is based on individuals' Equifax Risk Score and Age. We use the FRBNY Consumer Credit Panel (CCP)/Equifax data set, which comprises of a 5% random sample of individuals in the U.S. with a credit file and social security number. The dependent variable is $OutMigration$, an indicator variable that equals 1 if the individual in 2010 moved to a different county by 2019. The main independent variable is $SmokeChange$, calculated as average population-weighted cumulative smoke exposure in 2016–2019 minus its value in 2006–2009. $SmokeChange$ is standardized by subtracting its mean and then dividing the difference by its standard deviation. Each cell reports the point estimate of $SmokeChange$ for a different subsample regression based on a combination of age group and Equifax Risk Score group. Robust standard errors clustered by county are reported in parentheses. The stars *, **, ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table XI: Hospital Financial Summary Statistics

	Mean	Median	P25	P75	SD
$g(NFA)_{t+1}$	0.034	-0.013	-0.057	0.056	0.200
$g(NFA)_{t+2}$	0.079	-0.015	-0.094	0.125	0.361
$InvInc$	0.025	0.008	0.002	0.029	0.042
$FinInv$	0.535	0.265	0.069	0.756	0.694
$g(SRev)$	0.038	0.034	-0.009	0.080	0.088
$OpInc$	0.200	0.150	-0.046	0.379	0.471
$\log(TRev)$	4.553	4.570	3.461	5.613	1.313
Observations	6,937				

This table reports summary statistics for hospital financial variables from the HCRIS database. $g(NFA)_{t+1}$ and $g(NFA)_{t+2}$ are percentage change in hospital net fixed assets from year t to $t+1$ and $t+2$, respectively. $InvInc$ is the ratio of hospital investment income to previous year net fixed assets. $FinInv$ is the ratio of financial investment value to net fixed assets in the previous year. $g(SRev)$ is one-year growth in service revenue from year $t-1$ to t. $OpInc$ is the ratio of operating income to previous year net fixed assets. $\log(TRev)$ is the natural log of total revenue. P25, P75, and SD are the 25th percentile cutoff, 75th percentile cutoff, and standard deviation of the distribution of that variable.

Table XII: The Effects of Smoke Pollution on Hospital Investment

	(1) $g(NFA)_{t+2}$	(2) $g(NFA)_{t+2}$	(3) $g(NFA)_{t+1}$	(4) $g(NFA)_{t+1}$
$InvInc$	0.619***	0.635***	0.133	0.137
	(0.226)	(0.224)	(0.093)	(0.090)
$Smoke \times InvInc$	0.278**	0.267**	0.171*	0.169*
	(0.126)	(0.126)	(0.099)	(0.098)
$Smoke$	-0.023*	-0.024*	-0.012	-0.012
	(0.013)	(0.013)	(0.009)	(0.009)
$g(SRev)$	-0.078	-0.075	-0.044	-0.043
	(0.078)	(0.076)	(0.038)	(0.037)
$OpInc$	0.217***	0.216***	0.106***	0.104***
	(0.050)	(0.049)	(0.023)	(0.023)
$\log(TRev)$	-0.181	-0.189	-0.077	-0.079
	(0.142)	(0.128)	(0.050)	(0.048)
$FinInv$	0.173***	0.170***	0.098***	0.096***
	(0.039)	(0.039)	(0.019)	(0.019)
County Controls	No	Yes	No	Yes
State-Year FE	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes
Adj. R^2	0.280	0.281	0.147	0.147
N	6,384	6,384	6,333	6,333

This table reports ordinary least squares estimates of the effect of smoke pollution on hospital net fixed asset growth. In columns (1) and (2), the dependent variable is two-year percentage change in net fixed assets, and in columns (3) and (4), the dependent variable is one-year percentage change in net fixed assets. $Smoke$ is the standardized population-weighted cumulative amount of smoke $PM_{2.5}$ exposure during the county-year. $InvInc$ is the ratio of hospital investment income to previous year net fixed assets. The remaining control variables are described in the main text. Robust standard errors clustered by hospital and fiscal end year-month are reported in parentheses. The stars *, **, ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Internet Appendix for Up in Smoke: The Impact of Wildfire Pollution on Healthcare Municipal Finance

March 18, 2025

Appendix A. Hospital Intake

In this appendix, we show that wildfire smoke is associated with a significant increase in asthma cases, hospital ER visits, and hospital admissions. ER visits are associated with highly negative profit margins if the incoming patients are Medicare-insured, Medicaid-insured, or uninsured (Wilson and Cutler, 2014). In light of evidence that wildfire smoke pollution disproportionately affects older households and lower-income households, these results suggest that wildfire smoke reduces profit margins for hospitals, thereby increasing their credit risk.

Appendix A.1. Asthma Cases

Our first step is to test if wildfire smoke increases the likelihood of respiratory illness. We obtain data from the Centers for Disease Control and Prevention (CDC) and the 2020 Behavioral Risk Factor Surveillance System (BRFSS) on the number of asthma cases. The information on asthma cases is taken from state statistics on the burden of asthma among adults for those who answered "yes" to the questions: "Have you ever been told by a doctor or other health professional that you had asthma?" and "Do you still have asthma?"

We regress the number of asthma cases on our *Smoke* variable and include the country control variable vector Z from our baseline regression in the main text, in addition to state and year fixed effects. The results in Table A.1 indicate that adults are more likely to receive an asthma diagnosis during years with high levels of wildfire smoke pollution, which is consistent with findings in Noah et al. (2023) and Wilgus and Merchant (2024). In particular, column (1) indicates that a one standard deviation increase in *Smoke* is associated with approximately 9 additional asthma cases per 1,000 people annually. When we replace the state fixed effects with county fixed effects in column (2), the effect is slightly larger, with a point estimate of approximately 10 additional asthma cases per 1,000 people annually. Lastly, in column (3), we replace *Smoke* with *HomeSmoke* and *AwaySmoke*, and find that both measures are associated with a significant increase in asthma cases. Therefore, out-of-state wildfire smoke imposes negative health externalities on nearby states in addition to the negative financial externalities highlighted in the main text.

Appendix A.2. Hospital ER Visits and Admissions

The increase in respiratory problems is likely associated with an increase in costly ER visits to hospitals. To explore this idea, we collect annual state-level data on total emergency room visits and hospital admissions from the Kaiser Family Foundation (KFF), a non-profit organization for health policy research, and the American Hospital Association. We regress the number of ER visits per 1,000 people on *Smoke*, and also include the same controls from our asthma tests. The results in Table A.2, column (1) indicate that a one standard deviation increase in *Smoke* is associated with approximately 2.5 additional ER visits per 1,000 people annually.

In column (2) of Table A.2, we retest the same regression, except that we replace *Smoke* with *HomeSmoke* and *AwaySmoke*. In this case, we find that both measures are associated with significantly more ER visits (1.7 visits per 1,000 people and 2.2 visits per 1,000 people, respectively), indicating that out-of-state smoke also imposes real health externalities on neighboring states. Lastly, we repeat the tests in columns (1) and (2), except that we use hospital admissions per 1,000 people as the dependent variable. The results in columns (3) and (4) indicate that hospital admissions similarly increase in response to greater in-state or out-of-state wildfire smoke levels.

Economically, the increase in ER visits is associated with worse profit margins for hospitals. According to Dennin et al. (2025), senior citizens represent 16% of the U.S. population, but incur 75% of the health damages associated with wildfire smoke. According to Wilson and Cutler (2014), the average ER profit margin for Medicare-insured patients is -15.6%, while the average ER profit margin for the remaining patient categories is 17.4%. These figures imply that wildfire smoke damages are associated with a $-15.6\% \times 75\% + 17.4\% \times 25\% = -7.4\%$ average ER profit margin. For hospitals located in counties with more Medicare-insured, Medicaid-insured, and uninsured residents, the average ER profit margin will be lower again, thereby placing greater financial stress on hospitals located in counties with more socially vulnerable populations.

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Table A.1: The Effects of Smoke Pollution on Asthma Cases

	(1)	(2)	(3)
		Number of Asthma Cases (thousands)	
Smoke	8.842***	9.693***	
	(1.055)	(1.169)	
HomeSmoke			13.995***
			(1.633)
AwaySmoke			6.387***
			(0.732)
Controls	Yes	Yes	Yes
State FE	Yes	No	Yes
County FE	No	Yes	No
Year FE	Yes	Yes	Yes
Adj. R^2	0.992	0.991	0.99
N	21,700	21,700	19,002

This table reports ordinary least squares estimates of the effect of smoke pollution on asthma cases. The dependent variable is the number of asthma cases (in thousands). *Smoke* is the standardized population-weighted cumulative amount of smoke $PM_{2.5}$ exposure during the county-year. *HomeSmoke* is the standardized predicted component of *Smoke* based on a regression of *Smoke* on wildfire data specified in the text, and *AwaySmoke* is the standardized residual component from that regression. The information on asthma cases was taken from CDC statistics on the burden of asthma among adults, specifically for those who answered "yes" to the questions: (1) "Have you EVER been told by a doctor or other health professional that you had asthma?" and (2) "Do you still have asthma?" The control variables are specified in the main text. Robust standard errors clustered by county are reported in parentheses. The stars *, **, ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.2: The Effects of Smoke Pollution on Hospital Utilization

	(1) ER Visits	(2) ER Visits	(3) Admissions	(4) Admissions
Smoke	2.448***		0.361***	
	(0.152)		(0.024)	
HomeSmoke		1.718***		0.425***
		(0.216)		(0.023)
AwaySmoke		2.200***		0.123***
		(0.134)		(0.023)
Controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.921	0.930	0.967	0.970
N	36,973	32,871	36,973	32,871

This table reports ordinary least squares estimates of the effect of smoke pollution on hospital utilization. The dependent variables are the number of hospital ER visits and hospital admissions per 1,000 people at the state-level. *Smoke* is the standardized population-weighted cumulative amount of smoke $PM_{2.5}$ exposure during the county-year. *HomeSmoke* is the standardized predicted component of *Smoke* based on a regression of *Smoke* on wildfire data specified in the text, and *AwaySmoke* is the standardized residual component from that regression. The control variables are specified in the main text. Robust standard errors clustered by state are reported in parentheses. The stars *, **, ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.