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

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ABSTRACT

Industries face unique risks that can affect their cost of capital and investment. In healthcare, wildfire smoke pollution (*Smoke*) increases service demand, but the expected profit effect depends on the share of insured patients. We show that *Smoke* increases borrowing costs in the healthcare municipal bond market, especially in high-underinsurance counties. A natural experiment using the staggered expansion of Medicaid supports a causal interpretation. *Smoke* increases relative demand from underinsured patients and uncompensated care costs, further supporting the underinsurance channel. Hospitals respond by reducing investment. Out-of-state *Smoke* similarly increases borrowing costs, indicating unchecked wildfires impose negative externalities on other states.

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I. Introduction

Industries are exposed to unique cash flow risks that can shape their cost of capital and real investment activity in ways that the standard asset pricing models do not fully capture. In the healthcare industry, investors require a higher rate of return due to the risk that the federal government cuts funding for demand subsidy programs such as Medicare and Medicaid. Consequently, investment in research and development in the US healthcare sector has been roughly 50% lower due to this risk (Koijen, Philipson and Uhlig, 2016).

What drives differences in financial responses to risks specific to the healthcare industry remains unclear and underexplored. Take, for example, the proposed Clinton healthcare reforms in the early 1990s, which aimed to provide universal healthcare coverage and implement price controls. Koijen, Philipson and Uhlig (2016) show that the cost of capital in the healthcare industry was significantly higher during the prior two years of discussion, even though the reforms ultimately failed to pass Congress. The authors further show that the healthcare cost of capital was not affected by a similar risk event, the proposed Obama healthcare reforms in the late 2000s. These findings highlight the challenges associated with studying risks unique to specific industries.

We utilize an extensive panel of wildfire smoke pollution data from the Stanford Echo Lab to better understand how specific risks can uniquely affect the cost of capital and investment in the healthcare industry. This panel represents a continuum of recurring, plausibly exogenous shocks to demand for healthcare services. To provide some background, municipalities have been increasingly exposed to toxic particulate matter ($PM_{2.5}$) from wildfires over the last several decades. $PM_{2.5}$ exposure is associated with millions of deaths per year and increased emergency room (ER) visits for heart disease, asthma, and emphysema (Deryugina et al., 2019; Aguilera et al., 2021; Heft-Neal et al., 2023; Gould et al., 2024). In California alone, there was a 15-20% surge in hospitalizations due to $PM_{2.5}$ exposure in 2020, an especially active year for wildfires. Recent estimates indicate that wildfire smoke pollution is responsible for approximately 25% of US $PM_{2.5}$ exposure and 50% of $PM_{2.5}$ exposure in Western states (Burke et al., 2021).

Financially, hospitals have faced challenges absorbing the increased demand for ER services, especially non-profit hospitals which are more likely to admit underinsured patients. The average profit margin for ER admissions is 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). If $PM_{2.5}$ exposure persistently increases relative demand from underinsured patients, then hospitals may face solvency issues and lose access to capital markets. This is where our study comes in: we are the first to analyze how *Smoke* uniquely affects the cost of capital, investment, and service demand in the healthcare industry. This is crucial because restricted access to capital markets is in turn associated with reduced quality of care and increased mortality rates (Aghamolla et al., 2024).

The healthcare municipal bond offering market provides an ideal laboratory for testing the effect of wildfire smoke on the cost of capital in the healthcare industry because the associated borrowing costs (yields) are forward-looking and incorporate long-term expectations about the solvency of the underlying issuer. The healthcare municipal bond market also represents a primary source of financing for non-profit hospitals (about 70% of US hospitals), and the associated offering yields translate to direct costs for the issuer and indirect costs for the patient (AHA, 2017, 2025). With hospitals closing at a higher rate in recent years—particularly in rural areas (Kaufman et al., 2016; Cornaggia, Li and Ye, 2024)—and the high percentage of defaults in the healthcare municipal bond market relative to other sectors

(Gao, Lee and Murphy, 2019), it is more important than ever to understand the drivers of hospital credit risk and investment.

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 an 8.3 basis point (bps) increase in the average offering yield spread for healthcare municipal bonds, or $210 million in present value interest costs on the $25.4 billion of healthcare municipal bonds from above-mean *Smoke* counties. Based on current smoke trends, we predict another $630 million in present value interest costs over the next ten years. These findings are robust to including county fixed effects, state-year fixed effects, and controls for direct physical damages from local wildfires. Additional robustness tests indicate that our results are not affected by alternative measures of the yield spread or alternative approaches for clustering standard errors. Overall, these findings suggest that wildfire smoke is a unique risk for healthcare service providers that ultimately increases their cost of capital.

The effect of *Smoke* on healthcare borrowing costs is especially pronounced if a large number of underinsured patients reside in the county of issuance. Using insurance information from the US Census American Community Survey (ACS) database, we define individuals as underinsured if they are placed in the category of uninsured, Medicaid-insured, or Medicare-insured, as all three categories are associated with negative profit margins for hospitals. If the healthcare service provider is located in a high-underinsurance county, *Smoke* increases healthcare yields by an additional 3.8 bps relative to the baseline *Smoke* effect of 8.3 bps (46%). These findings support our proposed mechanism that healthcare credit risk increases because of *Smoke*-induced demand for healthcare services from unprofitable patient groups.

The staggered state-level expansion of Medicaid insurance eligibility sharpens the identification of the underinsurance channel. In June 2012, the Supreme Court ruled that states are not required to expand Medicaid eligibility under the Affordable Care Act, which was signed into law in 2010 during the Obama administration. Forty states have chosen to expand Medicaid at different times since that ruling, and a large percentage of uninsured residents in those states now have health insurance through the Medicaid program (Gao, Lee and Murphy, 2022). For hospitals, overall profitability from the underinsured category improved due to the expanded coverage. Importantly, we find that the incremental effect of *Smoke* on healthcare yields in high underinsurance counties is attenuated after the state expands Medicaid eligibility relative to states that have not. This finding further supports our proposed channel that *Smoke* affects healthcare yields due to unprofitable demand for healthcare services from underinsured patients.

A systematic analysis of ER visits further indicates that *Smoke* constitutes a unique risk for healthcare service providers. Using ER data from the Agency for Healthcare Research and Quality (AHRQ), we find that a one standard deviation increase in *Smoke* is associated with a 0.8% increase in ER visits from unprofitable underinsured residents, and a similar 0.8% increase in ER visits from profitable privately-insured patients. These effects translate to a significant increase in underinsured patients relative to privately insured patients, as patient discharges from the former group outnumber those from the latter group at an approximately three-to-one ratio. The asymmetric effect translates to financial losses for *Smoke*-affected healthcare service providers since ERs deliver about 50% of all hospital-associated medical care, and underinsured patients generate negative ER profit margins (Wilson and Cutler, 2014).

Related tests indicate that *Smoke* also significantly increases uncompensated care costs for healthcare service providers. Uncompensated care costs are mainly attributable to bad debt from uninsured patients and partial reimbursements from Medicaid and Medicare insurance providers. We conduct a systematic analysis of uncompensated care costs using data from the Centers for Medicare and Medicaid Services (CMS) Healthcare Cost Report Information System (HCRIS) database. We find that *Smoke* significantly increases uncompensated care costs for healthcare service providers, particularly in counties in the upper quartiles of underinsurance. Combined with our baseline findings, these results indicate that the municipal bond market assigns higher yields to hospitals that are expected to provide more unprofitable *Smoke*-related healthcare services.

The adverse financial effects from *Smoke* may translate to adverse real effects, especially if the hospital is already financially constrained (Stein, 2003; Adelino, Lewellen and Sundaram, 2015). Using fixed asset data from HCRIS, we find that a one standard deviation increase in *Smoke* is associated with a 2.0% reduction in fixed asset growth over one year and a 6.5% reduction in fixed asset growth over two years. These results suggest that the average hospital reduces real investment activity in response to *Smoke*-induced financial constraints.

Having established that *Smoke* increases the healthcare cost of capital and reduces investment growth, the next step in our analysis is to test if wildfire smoke imposes negative externalities on hospitals in nearby states. Environmental researchers have shows that wildfires generate smoke plumes that travel hundreds of miles, reducing 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 California wildfires over the past decade. Using wildfire data from the US Department of Homeland Security (DHS), we decompose *Smoke* into its in-state and out-of-state components (*HomeSmoke* and *AwaySmoke*). We find that the *AwaySmoke* effect on healthcare borrowing costs (7.8 bps) is statistically similar to the *HomeSmoke* effect (8.5 bps), indicating that wildfire smoke from other states is an important driver of healthcare credit risk.

Anecdotally, wildfires in California increased *Smoke* in Nevada by 2.5 standard deviations in 2020. Our *AwaySmoke* point estimate suggests that an average $90 million hospital issue in Nevada in 2020 would incur an additional $1.8 million in interest expenses.[1] Broadly, the *AwaySmoke* findings underline the importance of interstate coordination 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 interstate industrial pollution before being blocked by the Supreme Court in 2024 (AP News, 2024).

Lastly, we show that long-term concerns about wildfire smoke are reflected not only in healthcare municipal bond yields but also in migration patterns. Using household data from the Federal Reserve Bank of New York (FRBNY) Equifax Consumer Credit Panel (CCP), a sample of US 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 compared to individuals from other age or credit score groups. The resulting patient composition, therefore, skews more toward underinsured residents who are less likely to change address and more likely to have a low credit score (Mateyka and He, 2022), placing further stress on the finances of local healthcare providers.

II. Related Literature

The financial health economics theoretical framework in Koijen, Philipson and Uhlig (2016) provides useful context for our findings. In their model, healthcare securities receive price discounts for two reasons: (1) a reduction in expected cash flows due to the unique

[1]Supporting tests show that fire suppression expenditures per acre are significantly higher in California than in nearby states, while fire prevention expenditures are significantly lower. Related research finds that California has a "long history of underinvestment in prevention and mitigation" due to institutional and political frictions (Wara et al., 2020; Boxall, 2020), suggesting that the *AwaySmoke* borrowing cost externalities in Western states are partially attributable to these frictions.

risk that the federal government cuts healthcare reimbursements, and (2) a healthcare risk premium from a positive correlation between this risk and tighter federal government budget constraints. In our setting, we provide evidence of a price discount on healthcare municipal bonds due to the risk associated with wildfire smoke for healthcare service providers. As wildfire smoke tends to be localized to specific regions, the discount likely represents a reduction in expected cash flows, as local service providers 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 the federal government has tighter budget constraints.

From an empirical standpoint, our study contributes to the growing literature on the determinants of municipal borrowing costs. Local investors are important for pricing municipal bonds (Babina et al., 2021), and the associated borrowing costs are influenced by a variety of local factors such as state taxes (Garrett et al., 2023; Ambrose et al., 2025), 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), and age of the local tax base (Butler and Yi, 2022). 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.[2]

Lastly, our study builds on the literature on climate finance. Edmans and Kacperczyk

[2]Our study also relates to the empirical literature on hospital finance. Recent studies have shown that hospitals increase their use of more profitable treatment options after large financial losses (Adelino, Lewellen and McCartney, 2022); private equity buyouts of hospitals are associated with higher prices and insurance premiums (Liu, 2022; Aghamolla, Jain and Thakor, 2023); initial public offerings by hospitals lead to higher profits, net income, and net patient revenues (Aghamolla, Jain and Thakor, 2025); and gender differences do not affect decisions by hospital CEOs, even though female hospital CEOs earn lower salaries (Lewellen, 2025).

(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; Jha, Karolyi and Muller, 2025), but also from physical damage risk. In support of this latter channel, recent studies have shown that long-term municipal bond yields are affected by exposure to damage from rising sea levels (Painter, 2020; Goldsmith-Pinkham et al., 2023), heat stress (Acharya et al., 2022), and wildfires (Jeon, Barrage and Walsh, 2024). Additional studies similarly focus on the perceived risk of physical property damage (e.g., Baldauf, Garlappi and Yannelis, 2020; Auh et al., 2022; Bakkensen and Barrage, 2022; Nguyen et al., 2022; An, Gabriel and Tzur-Ilan, 2024; Jerch, Kahn and Lin, 2023; Bakkensen, Phan and Wong, 2024; Issler et al., 2024; Cookson, Gallagher and Mulder, 2024, 2025). We contribute to this literature by focusing on environmental health risks from wildfire smoke, which differ from physical damage risks associated with other climate events, and by highlighting the cost externalities for healthcare service providers.

III. Data and Summary Statistics

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. The proceeds code allows us to categorize bonds into two categories: (1) healthcare bonds, and (2) 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.[3] Lastly, we aggregate our observations to the issue level: 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, thereby allowing us to merge the municipal issue data with county-level wildfire smoke pollution data. We also supplement the Mergent database with county demographic data from the US Census Bureau's ACS database. 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, and (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 healthcare issues (Panel A) and non-healthcare issues (Panel B). The healthcare issues comprise 5.3% of the sample by total issue size. These issues have a mean offering yield spread of 120.1 bps, issue size of $63 million, maturity of 11.8 years, and rating number of 15.9 (approximately A2 on Moody's credit rating scale). Non-healthcare issues have lower average offering yield spreads, higher credit ratings, smaller issue sizes, and shorter maturities. These issues are also more likely to be general obligation or insured and less likely to be callable or issued in the negotiated market. In our subsequent tests, we control for these differences in issue characteristics.

[3]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.

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 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 $PM_{2.5}$ 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 $PM_{2.5}$ 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 in each county, where population shares are pegged to the 2014 ACS population 5-year estimates. Our second approach is to calculate the percentage of days in each year that a county had a "smoke day" in which at least 75% of its census tracts had a $PM_{2.5}$ concentration above zero.[4]

[4]Note that our measures of $PM_{2.5}$ exclude the $PM_{2.5}$ originating from non-wildfire sources. We refer to the wildfire smoke $PM_{2.5}$ measure from the Stanford Echo Lab as simply $PM_{2.5}$ for brevity and exposition.

We observe significant time series and cross-state variation in wildfire smoke pollution. Table II and Figure 1 provide summary statistics for our wildfire smoke pollution metrics by year. These statistics indicate that wildfire smoke pollution has been steadily trending upward over time, with large spikes in some years that double the amount of wildfire smoke pollution compared to 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 shifted to the Western US, with an exposure intensity spilling over to states in other regions.

C. Hospital and Insurance Data

We collect supplementary information on hospital finances, insurance coverage, and ER usage from several sources. First, we collect hospital-year data spanning 2012–2019 from the HCRIS database. This database contains detailed hospital financial information such as total revenue, total cost, total cost of uncompensated care, and fixed asset value.[5] Second, we collect information on county-level health insurance coverage from the American Community Survey (ACS) Small Area Health Insurance Estimates (SAHIE) database, which includes statistics on insured and uninsured patients in each county-year. Third, we collect US Census Bureau data on local health insurance statistics, including information on Medicare and Medicaid patients. Lastly, we collect annual ER data from the Healthcare Cost and Utilization Project (HCUP) Nationwide Emergency Department Sample (NEDS) database

[5]Processed HCRIS cost reports are available on the following website: `https://github.com/asacarny/hospital-cost-reports`. We thank Adam Sacarny for making this database publicly available.

for 35 states from 2009-2019. The NEDS database is the largest all-payer ER database in the US, comprising a stratified sample of about 20% of all hospital-based ERs. It contains data from approximately 33 million ER visits in 2019, or a weighted total of about 143 million visits. The NEDS database includes the expected payer status of each patient, specifically Medicare, Medicaid, private insurance, self-pay, and "no charge."

IV. Wildfire Smoke and Healthcare Borrowing Costs

A. *Baseline Analysis*

We begin by testing the effect of smoke pollution on the borrowing costs of healthcare 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:

$$y_{ijt} \;=\; \beta^H \cdot Smoke_{jt} \times Health_i + \beta^C \cdot Smoke_{jt} + \gamma \cdot X_{ijt} + \delta \cdot Z_{it} + \phi_{ijy} + \varepsilon_{ijt}, \qquad (1)$$

where $Health$ is an indicator variable that equals one if the municipal bond issue was used to finance a healthcare project. The β^C coefficient measures the effect of *Smoke* on non-healthcare yield spreads, and the β^H coefficient measures the incremental effect of *Smoke* on healthcare yield spreads, respectively. The issue-level control variable vector X consists of the standalone *Health* indicator variable, 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.[6] The county-level control variable vector Z consists of the natural logs of median household income and 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 $\times$ year and county fixed effects. Standard errors are clustered by state 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 an 8.3 bps increase in the relative offering yield spread for healthcare service providers, and no economically significant change for non-healthcare issues (0.8 bps). In column (2), we use industrial development bonds as our baseline instead of non-healthcare bonds and find stronger results (11.2 bps). In columns (3) and (4), we test the same regressions from column (1), except that we use an alternative smoke measure (*SmokeDays*). *SmokeDays* is 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 normalized by subtracting its mean of 38.9 days and dividing the difference by its standard deviation of 22.4 days. For these tests, we find statistically significant point estimates similar to those in the first two columns.

The borrowing cost effects are highly economically significant. For healthcare service providers, the 8.3 bps effect represents 9.3% of one standard deviation in the healthcare offering yield spread (88.9 bps), 8.9% of the credit spread between Aaa and Baa1 bonds (92.8

[6]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 before the financial crisis but higher yields after the crisis (Bergstresser and Pontiff, 2013; Wilkoff, 2013; Cornaggia, Hund and Nguyen, 2022).

bps), and \$210 million in additional present value interest costs on the \$25.4 billion worth of healthcare municipal bonds issued in above-mean *Smoke* counties. If average annual exposure to wildfire smoke pollution were to increase again by 72 $\mu g/m^3$ over the next decade based on current smoke trends (66.1% of one standard deviation in our cumulative $PM_{2.5}$ exposure measure), then our point estimates suggest that repeat issues of healthcare municipal bonds from our main sample period would amount to another \$630 million in out-of-sample present value interest costs.[7]

In Internet Appendix A, we analyze the dynamic effects of *Smoke* on healthcare yield spreads. Following Borgschulte, Molitor and Zou (2022), we include the lagged and lead values of *Smoke* (*LagSmoke* and *LeadSmoke*) in our baseline regression model. *LagSmoke* is used to examine the persistence of the *Smoke* effect on healthcare yields, while *LeadSmoke* is used as a "placebo" check on the effect of smoke from *next year* on healthcare yields from *this year*. The results in column (1) of Table A.1 indicate that *LagSmoke* does not affect healthcare yields, suggesting that the healthcare municipal bond market efficiently incorporates information from *Smoke* into yields. Column (1) indicates that *LeadSmoke* also does not affect healthcare yields, consistent with findings from Borgschulte, Molitor and Zou (2022) that wildfire smoke exposure events are quasi-randomly assigned.

Robustness tests in Internet Appendix A indicate that our baseline results are not affected by direct physical damages from wildfires or alternative definitions of the yield spread. In particular, columns (2) to (4) of Table A.1 show that our results remain highly robust to controlling for the number of wildfires in each county-year, the exclusion of any county-year

[7]The present value interest costs are calculated using the duration approximation formula: (1) \$210 million $\approx 0.00083 \times 10 \times$ \$25.4 billion, where 10 years is the average duration for a healthcare issue and the average *Smoke* value is approximately one for counties with above-mean *Smoke*, and (2) \$630 million $\approx 0.661 \times 0.00083 \times 10 \times$ \$115 billion, where \$115 billion is the total size of healthcare issues during our sample period.

in which at least one wildfire occurred, and the exclusion of California, where a significant percentage of wildfires occurred during our sample period. Lastly, in Table A.2, we show that our baseline results are unaffected if we use the tax-adjusted yield spread (Garrett et al., 2023) or call-adjusted yield spread (Novy-Marx and Rauh, 2012) as the dependent variable, exclude callable issues, focus on issues in the post-summer months of September to December. Our results are also unaffected if we cluster the standard errors by county and year-month.

B. Underinsurance Analysis

Our baseline findings indicate that *Smoke* increases borrowing costs for healthcare municipal bond issues. Our proposed mechanism for this finding is that the municipal bond market anticipates that *Smoke* will increase unprofitable demand for ER services from underinsured residents, thereby stressing healthcare finances and increasing healthcare credit risk. We first test the validity of this mechanism by testing the yield effect in the cross-section of underinsurance.

Methodologically, we collect county-year insurance information from the US Census Bureau's ACS database and define the underinsured population as the sum of uninsured, Medicaid-insured, or Medicare-insured residents. For our purposes, the latter two categories are included in the underinsured definition because the average ER profit margins associated with these categories are negative (Wilson and Cutler, 2014). We define *Underins* as the natural log of the average number of underinsured residents in the county, standardized across counties. We retest the regression model in equation (1) for the subsamples of above-median *Underins* ("high uninsurance") counties and below-median *Underins* ("low uninsurance") counties.

The results are reported in columns (1) and (2) of Table IV. These results indicate that a one standard deviation increase in *Smoke* is associated with a 9.0 bps increase in healthcare borrowing costs in high underinsurance counties, and a 6.7 bps increase in healthcare borrowing costs in low underinsurance counties. In column (3) of Table IV, we retest the regression model in equation (1) using our full sample of counties, except that we include the interactions of $Underins$ with $Health \times Smoke$, $Health$, and $Smoke$. The statistically significant point estimate on the triple interaction term indicates that a one standard deviation increase in *Smoke* is associated with an additional 3.8 bps increase in healthcare borrowing costs if $Underins$ is also one standard deviation higher than its mean. The results in this table indicate that the *Smoke* effect on healthcare borrowing costs is especially pronounced on the extensive margin of underinsurance.

C. Medicaid Expansion

Along the intensive margin, a higher expected reimbursement rate from underinsured patients may offset the stronger *Smoke*-yield effects observed in high-underinsurance counties. We test this prediction using the staggered expansion of Medicaid from 2012 to 2019 as part of the ACA. Testing this prediction sharpens identification of the underinsurance channel since the state-level decisions to expand Medicaid were uncorrelated with local economic conditions (Gao, Lee and Murphy, 2022).

To provide some background, the original ACA was signed into law in 2010 under the Obama administration. The law initially required states to expand their Medicaid eligibility ceilings to 138% of the federal poverty line (FPL) for all households, effectively reducing the share of uninsured residents within the underinsured category. Before the passage of the ACA, many states capped eligibility below the FPL and limited coverage to families with children.[8] Additionally, the ACA stipulated that the federal government would subsidize 90% of the cost of Medicaid expansion for each state in the long run, increasing reimbursement expectations for underinsured patients (Gao, Lee and Murphy, 2022).

In June 2012, the Supreme Court ruled in favor of the constitutionality of the ACA, but also ruled that states are not required to expand Medicaid eligibility under the ACA. Since that ruling, forty states have expanded Medicaid at different times, mainly due to political reasons (Gao, Lee and Murphy, 2022). Within those forty states, a significant number of eligible residents became Medicaid-insured after previously being uninsured. As a result, average hospital profit margins from underinsured patients improved, especially in high-underinsurance counties. Investors in the healthcare municipal bond market likely recognize that hospitals are more financially resilient to $Smoke$-induced shocks if a greater percentage of patients are Medicaid-insured as opposed to uninsured.

Methodologically, we test the same regression model as column (3) of Table IV for the following subsamples: $MedExp = 0$ (the state has not voted for Medicaid expansion as of that year-month) and $MedExp = 1$ (the state has voted for Medicaid expansion as of that year-month). The results are reported in columns (1) and (2) of Table V. For the $MedExp = 0$ subsample in column (1), the statistically significant point estimate on $Health \times Smoke \times Underins$ indicates that a one standard deviation increase in $Smoke$ is associated with an additional 6.1 bps increase in healthcare borrowing costs if $Underins$ is also one standard deviation higher than its mean. By contrast, for the $MedExp = 1$ subsample in column (2), the statistically insignificant point estimate on $Health \times Smoke \times Underins$ indicates that underinsurance does not exacerbate the $Smoke$ effect on healthcare yields.

[8]For reference, in 2009, the FPL was $10,830 for the first person in a household, and an additional $3,740 for each additional person in that household.

Lastly, in column (3) of Table V, we retest the regression model in column (1) of the same table, except that we use our full sample and include the interaction of $Health \times Smoke \times Underins$ with $MedExp$. (We also include the permutations of double-interactions and triple-interactions from these four variables.) Reflecting the evidence in the first two columns, we find that a one standard deviation increase in *Smoke* is associated with a 14.3 bps increase in healthcare borrowing costs in high underinsurance counties (8.1 bps + 6.2 bps). Importantly, the statistically significant point estimate on $Health \times MedExp \times Smoke \times Underins$ (-7.6 bps) indicates that the incremental 6.2 bps *Smoke* effect in high underinsurance counties is nullified by the expansion of Medicaid in that state. These findings indicate that an increase in the expected reimbursement rate from underinsured patients via Medicaid expansion partly offsets but does not eliminate the negative smoke effects on healthcare yields. One implication of this finding is that limiting access to Medicaid or reducing Medicaid reimbursement rates amplifies the adverse impact of wildfire smoke exposure on hospital borrowing costs.

V. Real Outcomes

The purpose of this section is threefold. First, we show that *Smoke* increases unprofitable ER visits to hospitals, thereby providing support for our proposed mechanism for how *Smoke* increases hospital credit risk. Second, using a panel of hospital-year data, we show that *Smoke* increases uncompensated care costs for hospitals, particularly in high-underinsurance counties, thereby "bridging the gap" between the increase in ER visits and the deterioration in credit risk. Lastly, using the same panel of hospital-year data, we demonstrate that the financial effects of *Smoke* are associated with reduced investment in hospital infrastructure in subsequent years, resulting in a reduction in real growth in the hospital industry.

A. *ER Admissions and Uncompensated Care*

The first step of our analysis of real outcomes is to test whether wildfire smoke increases hospital ER admissions. To do so, we obtain data on the number of ER admissions from AHRQ, which provides quarterly discharge data from emergency departments across 35 states from 2010 to 2019. We recalibrate our smoke measure to capture the standardized total population-weighted $PM_{2.5}$ exposure per quarter at the state level. We regress log ER admissions on *Smoke* while controlling for state and year-quarter fixed effects, and cluster the standard errors by state.

The results are reported in Panel A of Table VI. In column (1), we find that a one standard deviation smoke shock is associated with a statistically significant 0.9% increase in ER visits, or 2.7 ER visits per 10,000 capita relative to the average of 301 ER visits per capita. In California, which has a population of approximately 39.4 million people, a one standard deviation increase in *Smoke* would therefore be associated with about 10,600 additional quarterly ER visits. In columns (2) and (3), we examine ER visits based on the health insurance status of patients, and find that a one standard deviation increase in *Smoke* is associated with a similar percentage increase in ER visits from underinsured patients or privately-insured patients (0.8%). Lastly, in column (4), we show that the percentage change in underinsured ER visits is not significantly different from the percentage change in privately-insured ER visits. Overall, these results indicate that *Smoke* affects ER percentages about equally across insurance categories.[9]

[9] In Panel B of Table VI, we test the same regressions from Panel A, except that we use available data on pediatric asthma ER visits from AHRQ as the outcome variable. Consistent with evidence in Noah et al. (2023) and Wilgus and Merchant (2024), we find that *Smoke* is associated with a significant increase in

Back-of-the-envelope calculations indicate that these ER effects are associated with worse profit margins for hospitals, on average. According to AHRQ, approximately 75% of patient discharges are from the underinsurance category, while the remaining 25% are from the private-insurance category. That is, a hospital should expect three underinsured patients for every privately insured patient due to smoke-related illnesses. According to Wilson and Cutler (2014), the weighted-average profit margins for the underinsured and private-insured categories are -25.8% and 39.6%, respectively. Therefore, the average profit margin associated with a *Smoke* shock would equal $75\% \times -25.8\% + 25\% \times 39.6\% \approx -9.5\%$. (A hospital would require 40% of its patient discharges to come from the private-insured category to break even.) For high-underinsurance counties, the average *Smoke* effect on profit margins would therefore be more severe. For counties in states that expanded Medicaid, the average *Smoke* effect on profit margins would therefore be less severe since the average profit margin for the underinsured category improved following the expansion.

The idea that *Smoke* increases unprofitable ER visits from underinsured patients is reflected in hospital-year data on uncompensated care costs from HCRIS. These costs are mainly attributable to bad debt from uninsured patients and partial reimbursements from Medicaid and Medicare insurance providers. Methodologically, we take the ratio of uncompensated care costs to total revenue (UCR), and regress this outcome variable on *Smoke* for different underinsurance subsamples. For each of these regressions, we control for state $\times$ year and hospital fixed effects, and cluster the standard errors by state.

The results are reported in Table VII. In column (1), we focus on the subsample of counties in the top quartile of underinsurance. We find that a one standard deviation increase in *Smoke* is associated with a 0.45 percentage point increase in UCR, or 3.8% of the average

pediatric asthma ER visits. Consistent with Panel A, we also find that the percentage of pediatric asthma ER visits similarly increases across insurance categories.

UCR for this subsample. Within these counties, the ratio of underinsurance to private insurance is larger, and the increase in UCR reflects the higher expected *Smoke*-induced arrival of underinsured patients. In column (2), we find that a one standard deviation increase in *Smoke* is associated with a 0.30 percentage point decrease in UCR, or 3.5% of the average UCR for this subsample of counties. Within these counties, the ratio of underinsurance to private insurance is significantly smaller, and the decrease in UCR reflects the higher expected *Smoke*-induced arrival of privately insured patients. Lastly, in column (3), we regress UCR on *Smoke* and the interactions of *Smoke* with indicator variables for the top three quartiles of underinsurance, and similarly find that the *Smoke* effects are strongest in the upper two quartiles of underinsurance. Overall, this evidence indicates that *Smoke* imposes real costs on hospitals by increasing the arrival of underinsured patients.

B. Hospital Investment

Lastly, we analyze the effect of wildfire smoke pollution on real hospital investment spending. Intuitively, the adverse financial effects from *Smoke* may translate to adverse real effects through the investment channel, especially if the hospital is already financially constrained (Stein, 2003; Adelino, Lewellen and Sundaram, 2015). A *Smoke*-induced reduction in future investment would therefore suggest that *Smoke* exacerbates financial constraints for hospitals.

Adapting the methodology from Adelino, Lewellen and Sundaram (2015), we use hospital financial variables from the HCRIS database to test the effect of *Smoke* on non-profit hospital investment spending. The main dependent variables used for these tests 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 $g(NFA)_{h,j,t+2}$, and the main independent variable is *Smoke*. In a standard OLS regression that uses these variables as inputs, the point estimate on *Smoke* captures the effect of wildfire smoke pollution on future investment spending.

Formally, we test the following OLS regression model:

$$g(NFA)_{h,j,t+k} = \beta_1 \cdot Smoke_{j,t} + \delta \cdot X_{h,j,t} + \phi_{ijy} + \varepsilon_{h,j,t}, \tag{2}$$

where $k \in \{1, 2\}$, $g(NFA)_{h,j,t+k}$ is the future k-year growth rate in net fixed assets for hospital h in county j and year t, and ϕ_{ijy} is a vector of state $\times$ year and hospital fixed effects. 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. The summary statistics in Table VIII indicate that the variable distributions are similar to those reported in Adelino, Lewellen and Sundaram (2015).

The regression results are reported in Table IX. Column (1) indicates that a one standard deviation increase in *Smoke* is associated with a 2.0 percentage point decrease in one-year fixed asset growth, and column (2) indicates that the results are similar if we include the county control variables from our baseline regressions. Column (3) further indicates that a one standard deviation increase in *Smoke* is associated with a 6.5 percentage point decrease in two-year fixed asset growth, and column (4) indicates that the results are again similar if we include the county control variables from our baseline regressions. The stronger effect for two-year fixed asset growth reflects findings in Adelino, Lewellen and Sundaram (2015) that hospital investments are highly capital-intensive and require longer adjustment times.

Overall, the evidence from these tests indicates that wildfire smoke not only increases the cost of capital for hospitals but also exacerbates their financial constraints and reduces their investment activity over longer horizons.

VI. Cross-Border Externalities and Migration

A. Out-of-State Wildfire Smoke

A lack of state-level investment in wildfire prevention can increase the amount of wildfire smoke in nearby states, thereby imposing costly externalities on their healthcare systems. This section analyzes 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 DHS National Incident Management System/Incident Command System (ICS). We model the *Smoke* process as follows:

$$Smoke_{jsy} = \beta \cdot F_{sy} \times \delta_s + \gamma \cdot F_{sy} + \delta_s + \varepsilon_{jsy}, \tag{3}$$

where F_{sy} 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.[10] To account for variation in state-level smoke predictability due to geographic factors such as weather, we interact the F_{sy} 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

[10] To identify wildfire burn perimeters, we merge the ICS data with the US Forest Service Monitoring Trends in Burn Severity database, which records the geospatial area of wildfires (Eidenshink et al., 2007).

of interpretation, each variable is standardized by subtracting its mean and dividing the difference by its standard deviation.

We retest the baseline regression model in equation (1), except that we replace the *Smoke* variable with *HomeSmoke* and *AwaySmoke*. The results are reported in column (1) of Table X. We find that *HomeSmoke* and *AwaySmoke* significantly increase healthcare borrowing costs. Specifically, a one standard deviation increase in *HomeSmoke* is associated with an 8.5 bps increase in healthcare borrowing costs, and a one standard deviation increase in *AwaySmoke* is associated with a 7.8 bps increase in healthcare borrowing costs. We find that the *HomeSmoke* coefficient is also not statistically different from the *AwaySmoke* coefficient. In column (2), we retest 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-state and out-of-state wildfire smoke 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. 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 X indicate that healthcare borrowing costs would have increased by $7.8 \times 2.5 = 19.5$ bps due to the out-of-state smoke. For a hospital issue with an average size of \$90 million and a duration of ten years, the out-of-state smoke effect would increase total present value interest costs by about \$1.8 million.

Should we classify the *AwaySmoke* effects as cross-state negative externalities or spillovers? If a state spends less on 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 Internet Appendix B, we provide a case study discussion and analysis of wildfire prevention and suppression expenditures in California, where a large percentage of drifting wildfire smoke plumes currently originate in the US. Relative to other states in the Western US, California spends significantly more on wildfire suppression per acre and significantly less on wildfire prevention per acre. While a causal analysis of wildfire prevention expenditures and $AwaySmoke$ is outside the scope of this study, these results suggest that a lack of prevention expenditures imposes costly externalities on nearby states by increasing the healthcare cost of capital.

B. Long-Term Migration Patterns

Lastly, we analyze whether smoke-induced migration patterns could exacerbate the healthcare borrowing cost effects documented in our baseline analysis. Specifically, we examine the long-term impact of wildfire smoke pollution exposure on county population stock and county population flow. 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 residents. 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 (Mateyka and He, 2022). 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 (Wilson and Cutler, 2014).

Focusing on long-term residential sorting, we calculate the percentage change in the population stock from 2009 to 2019 ($\%PopChange_{js}$) in county j and state s using population estimates from the ACS. Similar to Childs et al. (2022), we also calculate $SmokeChange_{js}$ as the standardized county-level average cumulative $PM_{2.5}$ exposure from wildfire smoke pollution in 2016–2019 minus the county-level average in 2006–2009. Methodologically, we test a cross-sectional regression $\%PopChange_{js}$ on $SmokeChange_{js}$ and a vector of state fixed effects.

The results are reported in column (1) of Table XI. 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. In columns (2) and (3), we additively separate the outcome variable from column (1) into the change attributed to residents below 65 years of age and the change attributed to residents aged 65 years or older. We find that a one standard deviation increase in $SmokeChange$ is associated with a 0.78% decline in the younger population subgroup and no change in the older population subgroup, indicating that the $Smoke$-induced migration behavior is not uniform across age groups. Lastly, column (4) indicates that the effect in column (2) is statistically significant from the effect in column (3). These results suggest that the hospital patient mix in high-smoke areas tends to skew more toward older residents in the long run due to the out-migration of younger residents, thereby placing additional financial stress on healthcare service providers.

Credit score is another important factor that influences migration patterns. 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 sample of Equifax credit report data containing 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, $OutMigration_{ij}$ is an indicator variable that equals one 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 XII and graphically in Figure 4. The strongest smoke effect on out-migration is among individuals aged 20-40 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 percentage point increase in out-migration over ten years. On a relative basis, this effect is statistically larger than the *SmokeChange* effect for individuals aged 20-40 year in the lowest Equifax Risk Score group (0.5 percentage points). We also observe statistically significant effects for individuals aged 40-65 in the highest or second-highest Equifax Risk Score groups (1.1 and 1.0 percentage points, respectively). These results indicate that wildfire smoke is more likely to drive away younger, productive residents with strong credit scores, skewing the patient composition toward the remaining age and credit score groups.[11] Because many older residents are Medicare-insured and many low-credit residents are uninsured or Medicaid-insured, hospitals in high-smoke areas are also exposed to greater financial stress through the migration channel in the long run.

VII. Conclusion

Large-scale wildfires have become increasingly common over the last several decades, and the physical damage to areas in the associated burn regions is unprecedented. Municipalities downwind of wildfires may not suffer any physical damages, but they do incur the health and economic costs associated with poor air quality, even when the origin of the fire is in another state or country. These costs are expected to increase in many regions as air quality deteriorates.

Wildfire smoke pollution is a risk that uniquely affects the healthcare industry because it increases demand for healthcare services, regardless of insurance status. We estimate the 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

[11] These results complement findings in van Binsbergen et al. (2024) showing that toxic emissions from industrial plants reduce local real estate prices and consequently increase the proportion of residents in minority groups with lower credit scores. In our setting, the proportion of residents with lower credit scores increases because wildfire smoke drives away residents with higher credit scores.

associated with significantly higher borrowing costs for healthcare service providers (8.3 bps), especially in high-underinsurance counties where *Smoke*-induced demand for healthcare services is highly unprofitable. A natural experiment involving the expansion of Medicaid insurance eligibility and an increase in the expected reimbursement rate from underinsured patients supports a causal interpretation of the underinsurance channel. Underlining this channel, we document that *Smoke* is associated with a greater influx of underinsured patients and increased uncompensated care costs for hospitals. The adverse financial effects of *Smoke* on the healthcare industry translate to adverse real effects in the form of reduced investment growth. Out-of-state *Smoke* similarly increases the cost of capital for healthcare service providers, suggesting that a lack of investment in wildfire prevention at the state level can impose costly externalities on nearby states.

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 split the associated prevention and suppression costs optimally. 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 cannot negotiate 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 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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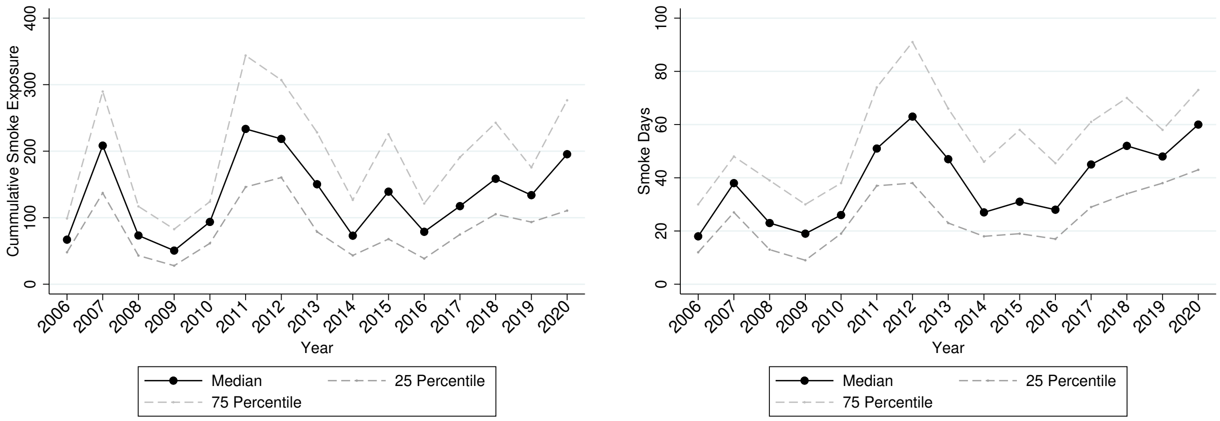
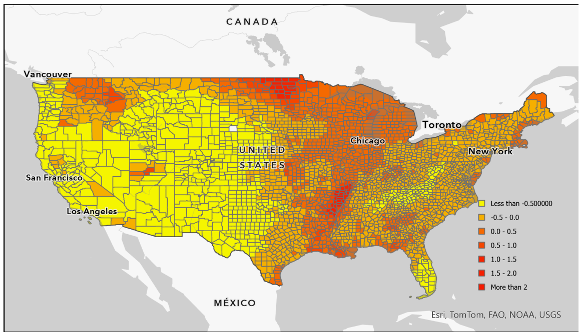


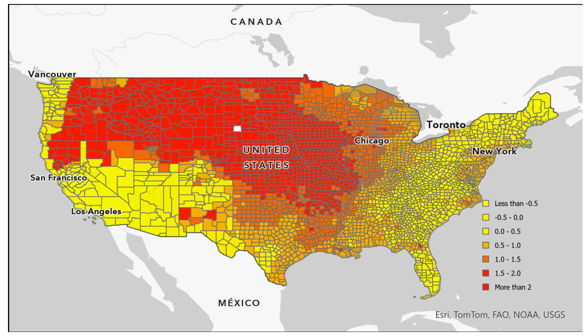
(a) Smoke Exposure (b) Smoke Days

Figure 1. U.S. Wildfire Smoke by Year

These figures provide time-series statistics on county-level cumulative wildfire smoke exposure and the 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



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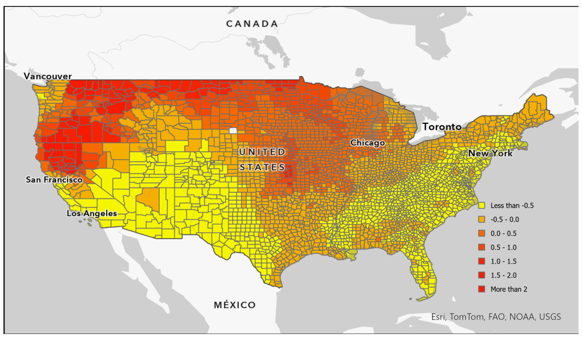
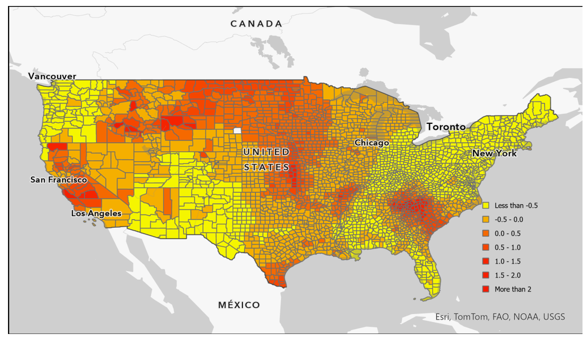


(c) 2014



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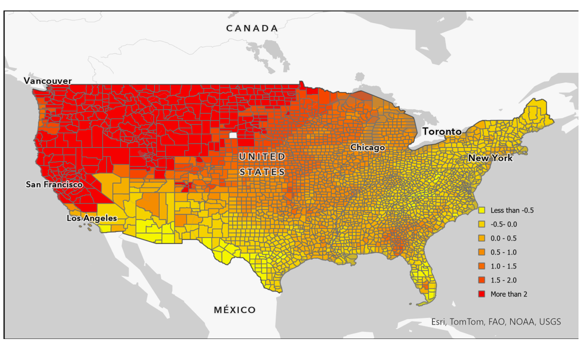

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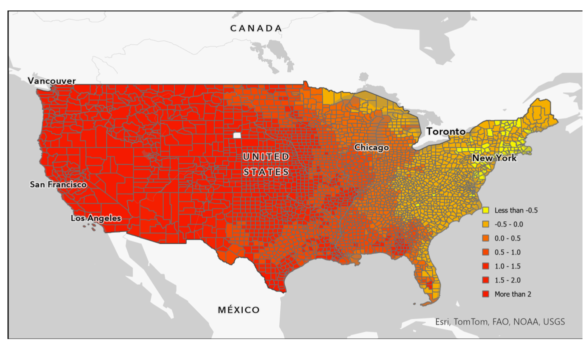
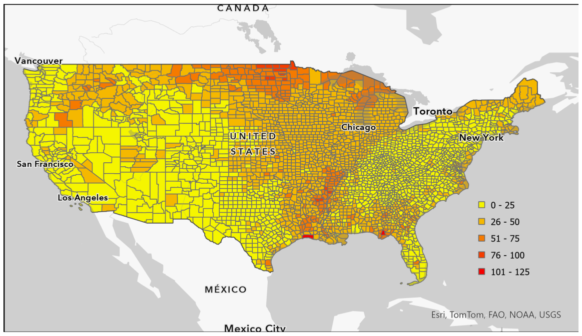


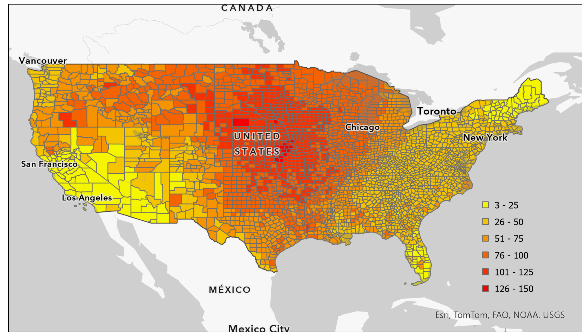
(f) 2020

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



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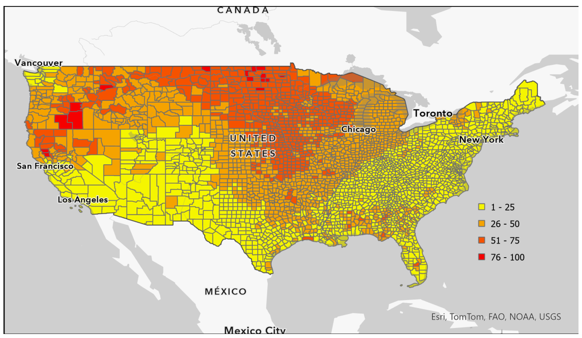

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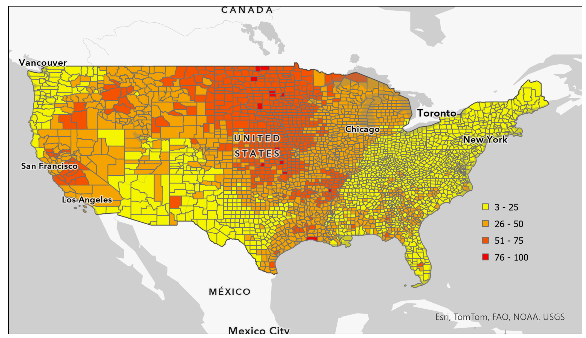

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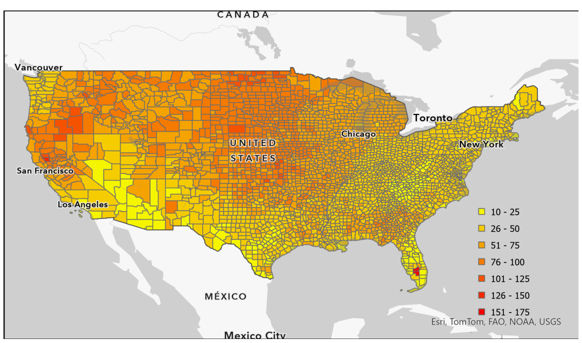

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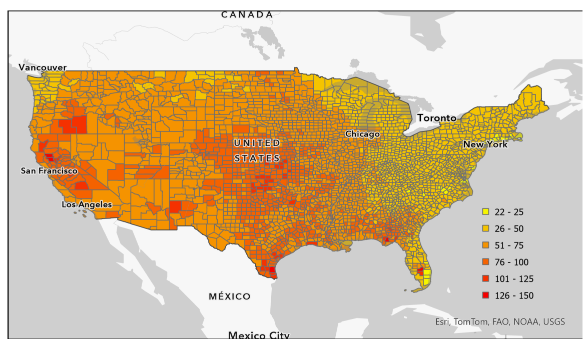

(f) 2020

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).

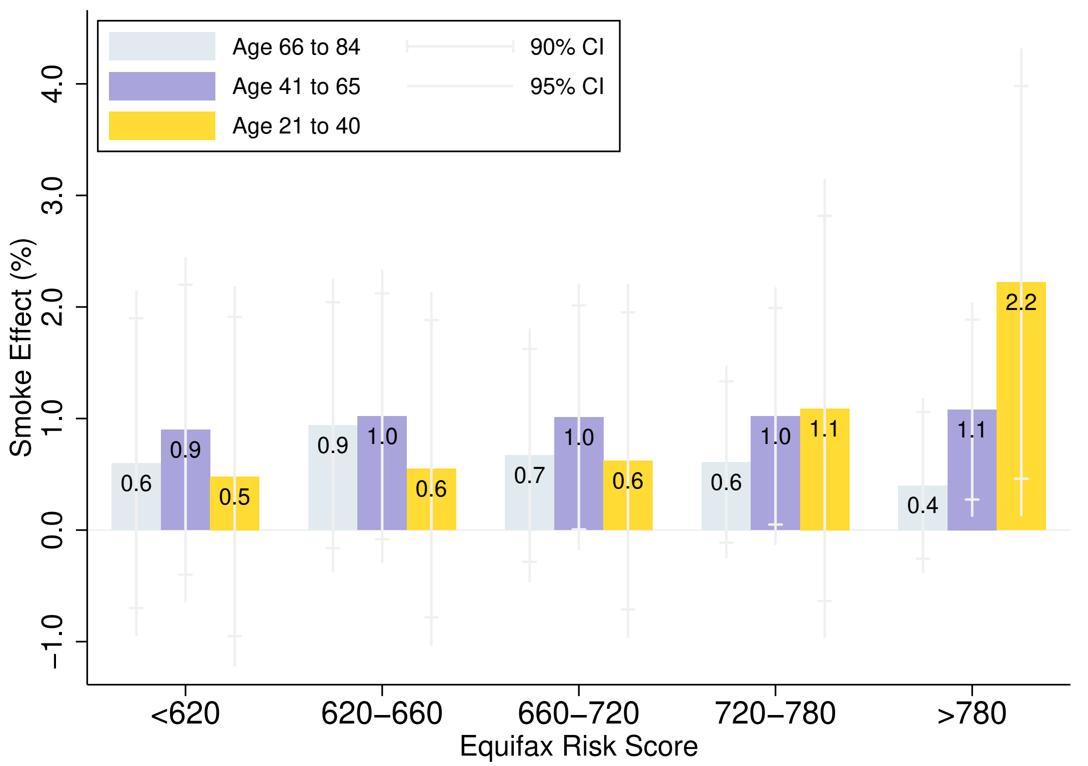

Figure 4. The Effects of Smoke Pollution on Out-Migration by Age and Credit Score

This figure reports point estimates from linear probability model OLS regressions of $OutMigration$ on $SmokeChange$ 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 the 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: Healthcare Issues

	Mean	Median	P25	P75	SD
Yield Spread (%)	1.201	1.063	0.564	1.780	0.889
Issue Size (M)	63.104	28.540	8.090	74.590	98.303
Years to Maturity	11.784	10.506	8.061	13.727	6.718
Rating Number	15.884	16.000	14.000	18.000	2.605
Unrated	0.344	0.000	0.000	1.000	0.475
General Obligation	0.153	0.000	0.000	0.000	0.360
Insured	0.034	0.000	0.000	0.000	0.182
Callable	0.913	1.000	1.000	1.000	0.281
Negotiated	0.770	1.000	1.000	1.000	0.421
N	1,467				

Panel B: Non-Healthcare Issues

	Mean	Median	P25	P75	SD
Yield Spread (%)	0.317	0.231	-0.019	0.557	0.576
Issue Size (M)	21.987	6.930	2.980	16.250	66.956
Years to Maturity	7.789	7.834	4.799	10.484	4.620
Rating Number	18.418	19.000	17.000	20.000	1.848
Unrated	0.264	0.000	0.000	1.000	0.441
General Obligation	0.677	1.000	0.000	1.000	0.468
Insured	0.146	0.000	0.000	0.000	0.353
Callable	0.716	1.000	0.000	1.000	0.451
Negotiated	0.299	0.000	0.000	1.000	0.458
N	75,330				

This table reports summary statistics for healthcare municipal bond issues (Panel A) and non-healthcare municipal bond issues (Panel B) 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 Sp. (%)	(2) Yield Sp. (%)	(3) Yield Sp. (%)	(4) Yield Sp. (%)
Smoke	0.008**	0.001		
	(0.004)	(0.015)		
Health × *Smoke*	0.083***	0.112***		
	(0.024)	(0.029)		
SmokeDays			0.016	0.012
			(0.010)	(0.021)
Health × *SmokeDays*			0.081***	0.117***
			(0.025)	(0.029)
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	0.582	0.643	0.582	0.643
N	76,522	28,537	76,522	28,537

This table reports OLS 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*, which are interacted with the *Health* indicator variable. *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 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 state and issuance year-month are reported in parentheses. The stars *, **, ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table IV: Wildfire Smoke Pollution Effects by Underinsurance Group

	(1) Yield Spread (%)	(2) Yield Spread (%)	(3) Yield Spread (%)
Smoke	0.013**	0.001	0.008**
	(0.006)	(0.007)	(0.004)
Health × *Smoke*	0.090***	0.067**	0.091***
	(0.028)	(0.031)	(0.028)
Underins × *Smoke*			0.008**
			(0.004)
Health × *Smoke* × *Underins*			0.038**
			(0.018)
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
Subsample	High Underins.	Low Underins.	Full
Adj. R^2	0.626	0.550	0.582
N	38,427	38,075	76,495

This table reports OLS estimates of the effects of smoke pollution on municipal borrowing costs in the cross-section of county underinsurance. The dependent variable is offering yield spread (%), and the main independent variables are the interactions of *Smoke* with the *Health* indicator variable and the *Underins* variable. *Smoke* is the standardized population-weighted cumulative amount of smoke $PM_{2.5}$ exposure during the county-year. *Underins* is the standardized log average number of underinsured residents in that county. A resident is underinsured if they are uninsured, Medicaid-insured, or Medicare-insured. In columns (1) and (2), we use subsamples of counties with above-median and below-median *Underins*, respectively. In column (3), we use the full sample of counties and interaction *Health* × *Smoke* with *Underins*. 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: Wildfire Smoke Pollution Effects and Medicaid Expansion

	(1) Yield Sp. (%)	(2) Yield Sp. (%)	(3) Yield Sp. (%)
$Smoke$	0.007	0.003	0.003
	(0.008)	(0.007)	(0.008)
$Health \times Smoke$	0.083**	0.100***	0.081**
	(0.036)	(0.036)	(0.035)
$Underins \times Smoke$	0.007	0.003	0.009**
	(0.005)	(0.005)	(0.004)
$Health \times Smoke \times Underins$	0.061***	-0.023	0.062***
	(0.021)	(0.033)	(0.020)
$Health \times MedExp \times Smoke$			0.028
			(0.041)
$Health \times MedExp \times Smoke \times Underins$			-0.076**
			(0.036)
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
Subsample	NoMedExp	PostMedExp	Full
Adj. R^2	0.550	0.624	0.583
N	42,914	33,292	76,495

This table reports OLS estimates of the effects of smoke pollution on municipal borrowing costs as functions of county underinsurance and state-level Medicaid expansion. The dependent variable is offering yield spread (%), and the main independent variables are the interactions of $Smoke$ with the $Health$ indicator variable, the $Underins$ variable, and the $MedExp$ indicator variable. $Smoke$ is the standardized population-weighted cumulative amount of smoke $PM_{2.5}$ exposure during the county-year. $Underins$ is the standardized log average number of underinsured residents in that county. A resident is underinsured if they are uninsured, Medicaid-insured, or Medicare-insured. $MedExp$ is an indicator variable that equals one after the state chooses to expand Medicaid coverage under the Affordable Care Act. In columns (1) and (2), we use subsamples of county-years in which the associated state has not expanded Medicaid, and county-years in which the associated state has expanded Medicaid. In column (3), we use the full sample of counties and interaction $Health \times Smoke$ with $Underins$ and $MedExp$. 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 VI: The Effects of Smoke Pollution on Adult and Pediatric ER Admissions

Panel A: Adult and Pediatric ER Visits

	(1) ln(ER)	(2) ln(ER_{under})	(3) ln($ER_{private}$)	(4) ln($ER_{under}/ER_{private}$)
Smoke	0.009**	0.008**	0.008*	-0.000
	(0.004)	(0.004)	(0.004)	(0.004)
Insurance Status	Any	Underins.	Private	Any
State FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Adj. R^2	0.997	0.996	0.993	0.887
N	1,228	1,228	1,228	1,228

Panel B: Pediatric ER Asthma Visits

	(1) ln(ER)	(2) ln(ER_{under})	(3) ln($ER_{private}$)	(4) ln($ER_{under}/ER_{private}$)
Smoke	0.053***	0.050***	0.056***	-0.006
	(0.015)	(0.015)	(0.018)	(0.011)
Insurance Status	Any	Underins.	Private	Any
State FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Adj. R^2	0.986	0.980	0.972	0.767
N	1,228	1,227	1,227	1,227

This table reports OLS estimates of the effect of smoke pollution on total state-quarter ER visits by insurance type of the admitted patient from 2010 to 2019. Panel A focuses on all adult and pediatric ER visits, and Panel B focuses on pediatric asthma ER visits. The dependent variable is the natural log of state-quarter ER visits. ER_{under} represents ER visits from Medicare-insured, Medicaid-insured, or uninsured patients. $ER_{private}$ represents ER visits from privately-insured patients. *Smoke* is the standardized population-weighted cumulative amount of smoke $PM_{2.5}$ exposure during the state-year-quarter. Robust standard errors clustered by state are reported in parentheses. The stars *, **, ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively. ER Data Source: Agency for Healthcare Research and Quality.

Table VII: The Effects of Smoke Pollution on Hospital Uncompensated Care Costs

	(1) UCR	(2) UCR	(3) UCR
Smoke	0.446**	-0.295*	-0.346**
	(0.218)	(0.174)	(0.151)
Underins Q2 × *Smoke*			0.265
			(0.167)
Underins Q3 × *Smoke*			0.391*
			(0.201)
Underins Q4 × *Smoke*			0.641***
			(0.191)
Subsample	Underins. Q4	Underins. Q1	Any
State-Year FE	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes
Adj. R^2	0.709	0.738	0.743
N	5,007	6,166	21,397

This table reports OLS estimates of the effect of smoke pollution on hospital uncompensated care costs. UCR is the total cost of uncompensated care as a percentage of total hospital revenue. In columns (1) and (2), we focus on counties in fourth quartile of $Underins$ and the first quartile of $Underins$, respectively. $Smoke$ is the standardized population-weighted cumulative amount of smoke $PM_{2.5}$ exposure during the county-year. Robust standard errors clustered by hospital are reported in parentheses. The stars *, **, ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively. Source: Healthcare Cost Report Information System (HCRIS) and Adam Sacarny's website.

Table VIII: Hospital Financial Summary Statistics

	Mean	Median	P25	P75	SD
$g(NFA)_{t+1}$	0.042	-0.013	-0.058	0.058	0.278
$g(NFA)_{t+2}$	0.092	-0.016	-0.098	0.127	0.489
$FinInv$	0.559	0.269	0.069	0.766	0.767
$g(SRev)$	0.037	0.034	-0.010	0.081	0.093
$OpInc$	0.201	0.146	-0.054	0.385	0.640
$\log(TRev)$	4.461	4.482	3.342	5.564	1.359

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. $FinInv$ 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 operating income ratio to the previous year's net fixed assets. Log $(TRev)$ is the natural log of total revenue.

Table IX: The Effect of Smoke Pollution on Hospital Investment

	(1) $g(NFA)_{t+1}$	(2) $g(NFA)_{t+1}$	(3) $g(NFA)_{t+2}$	(4) $g(NFA)_{t+2}$
Smoke	-0.020**	-0.019**	-0.065**	-0.064**
	(0.010)	(0.010)	(0.025)	(0.025)
Hospital Controls	Yes	Yes	Yes	Yes
County Controls	No	Yes	No	Yes
State-Year FE	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes
Adj. R^2	0.073	0.074	0.238	0.240
N	9,388	9,388	9,503	9,503

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

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

	(1) Yield Spread (%)	(2) Yield Spread (%)
$Health \times HomeSmoke$	0.085***	0.119***
	(0.029)	(0.032)
$Health \times AwaySmoke$	0.078***	0.089***
	(0.022)	(0.029)
$AwaySmoke$	0.005	-0.000
	(0.003)	(0.014)
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	0.646
N	65,032	22,997

This table reports OLS 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 the interactions of $HomeSmoke$ and $AwaySmoke$ with $Health$. $Smoke$ 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 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 state and issuance year-month are reported in parentheses. The stars *, **, ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table XI: The Effects of Smoke Pollution on County Population

	(1) $\%PopChange$	(2) $\%PopChange < 65$	(3) $\%PopChange \geq 65$	(4) Δ%PopChange
$SmokeChange$	-0.684*	-0.775**	0.092	-0.867*
	(0.390)	(0.382)	(0.168)	(0.443)
State FE	Yes	Yes	Yes	Yes
Population	Total	Young	Elderly	Total
Adj. R^2	0.140	0.121	0.177	0.111
N	3106	3106	3106	3106

This table reports OLS estimates of the effect of smoke pollution on migration using county-level data from the US Census Bureau American Community Survey. 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. In column (4), the dependent variable is the difference in the dependent variables between columns (2) and (3). $SmokeChange$ 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 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.

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

Equifax Risk Score	(1) Age 20-40	(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
Above 780 – Below 620	0.017***	0.002**	-0.002

This table reports linear probability model OLS estimates of the effect of wildfire smoke pollution on out-migration. Each subgroup is based on the individual's Equifax Risk Score and age. We use the FRBNY Consumer Credit Panel (CCP)/Equifax data set, which comprises a 5% random sample of US individuals with a credit file and social security number. The dependent variable is $OutMigration$, an indicator variable that equals one 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 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. In the last row, we test if the difference between the "Above 780" and "Below 620" point estimates is statistically significant. Robust standard errors clustered by county are reported in parentheses. The stars *, **, ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

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

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INTERNET APPENDIX

This Appendix provides supplemental results to accompany the manuscript "Up in Smoke: The Impact of Wildfire Pollution on Healthcare Municipal Finance."

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Appendix A.1. Supporting Tests

Following Borgschulte, Molitor and Zou (2022), we analyze the dynamic effects of *Smoke* on healthcare yield spreads. In particular, our baseline regression model includes the lagged and lead values of *Smoke* (*LagSmoke* and *LeadSmoke*). *LagSmoke* is used to examine the persistence of the *Smoke* effect on healthcare yields, while *LeadSmoke* is used as a "placebo" check on the effect of smoke from *next year* on healthcare yields from *this year*. The results in column (1) of Table A.1 indicate that *LagSmoke* does not affect healthcare yields, suggesting that the healthcare municipal bond market efficiently incorporates information from *Smoke* into yields. Column (1) indicates that *LeadSmoke* also does not affect healthcare yields, consistent with findings from Borgschulte, Molitor and Zou (2022) that wildfire smoke-exposure events are quasi-randomly assigned.

We also show that direct physical damage from wildfires does not affect our baseline results. In particular, in columns (2) to (4) of Table A.1, we show that our results remain highly robust to controlling for the number of wildfires in each county-year, the exclusion of any county-year in which at least one wildfire occurred, and the exclusion of California, where a significant percentage of wildfires occurred during our sample period.

We further show that our baseline results are qualitatively unaffected if we use alternative constructions of the yield spread or post-summer months of the year only. First, using the methodology in Garrett et al. (2023), we adjust each offering yield for the top marginal federal income tax rate since interest on municipal debt is federal tax deductible, and also the top marginal state income tax rate since interest on municipal debt is state tax deductible for in-state investors (excluding Illinois, Iowa, Oklahoma, and Wisconsin, where interest is not state tax deductible). The results in column (1) of Table A.2 indicate that our baseline results are stronger if we use the tax-adjusted yield spread instead. Second, using the methodology in Novy-Marx and Rauh (2012), we adjust each offering yield for call features, thereby decreasing the average offering yield spread for callable bonds. The results in column (2) indicate that our baseline results are similar if we use the call-adjusted yield spread instead. Third, we drop all callable issues and show in column (3) of Table A.2 that our results are similar, even with the reduced sample size. In column (4), we re-test our baseline regression model using only issues from the fourth quarter of the year when the wildfire season has largely concluded. and we find similar results. In unreported results, we also find that the standard errors are similar if we alternatively double-cluster the standard errors by county and year-month.

Appendix A.2. Externalities

In this appendix, we discuss whether the *AwaySmoke* effects documented in Section VI.A should be classified as cross-state negative externalities or spillovers. 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 prevention and mitigation," and "lacks a cost-benefit framework in which to evaluate prevention and mitigation investments against suppression investments" (Wara et al., 2020). A related Los Angeles Times article argues that this problem is 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" (Boxall, 2020). The same article notes that the state also canceled 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 that were meant for community protection and wildland fuel reduction.

We provide evidence that wildfire prevention expenditures are significantly lower in California compared to other states. In particular, we collect panel data on wildfire prevention expenditures from the USDA Forest Service, including information on all activities and costs of reducing hazardous fuel treatment on federal lands. Using these data, we calculate the state-year wildfire prevention expenditure per acre (*Prevention/Acre*). Our regression results in columns (1) and (2) of Table A.3 indicate that California spends about $334 less on wildfire prevention per acre, compared to an average of $370 per acre in the remaining states, even after controlling for the number of wildfires and the number of structures damaged in the state.

Lastly, we provide evidence showing that California spends more on wildfire suppression than other states, perhaps due to its relative lack of spending on wildfire prevention. We collect 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 calculate the state-year expenditure on wildfire suppression per burned acre (*StateSuppr/Acre*), and state-year federal expenditure on wildfire suppression per burned acre (*FedSuppr/Acre*). Our regression results in columns (3) and (4) of Table A.3 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. Related findings in columns (5) and (6) indicate 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 relatively low spending on prevention and high expenditure on 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).

Table A.1: Robustness Tests for Baseline Regressions

	(1) Yield Sp. (%)	(2) Yield Sp. (%)	(3) Yield Sp. (%)	(4) Yield Sp. (%)
Smoke	0.008**	0.009**	0.002	0.008
	(0.004)	(0.004)	(0.005)	(0.006)
Health × *Smoke*	0.080***	0.084***	0.091***	0.090***
	(0.021)	(0.024)	(0.027)	(0.025)
LagSmoke	0.006			
	(0.006)			
Health × *LagSmoke*	0.006			
	(0.024)			
LeadSmoke	0.002			
	(0.004)			
Health × *LeadSmoke*	0.005			
	(0.023)			
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
Model	Lead/Lag	Fire Control	Fire Excluded	CA Excluded
Adj. R^2	0.582	0.582	0.580	0.577
N	76,522	76,522	72,899	71,499

We retest our baseline regression model in equation (1) with the following modifications: in column (1), we include the one-year lag and lead values of *Smoke* as right-hand-side variables (*LagSmoke* and *LeadSmoke*) and their interactions with *Health*; in column (2), we include the county-year number of wildfire events as a control variable; in column (3), we instead exclude any county-year that experienced a wildfire event; in column (4), we exclude all counties in the state of California. Robust standard errors clustered by state and issuance year-month are reported in parentheses. The stars *, **, ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.2: Additional Robustness Tests for Baseline Regressions

	(1) y (Tax Adj.)	(2) y (Call Adj.)	(3) y (No Call)	(4) Yield Sp. (%)
Smoke	0.021***	0.009**	0.002	0.015***
	(0.007)	(0.004)	(0.007)	(0.004)
Health × *Smoke*	0.156**	0.070***	0.082**	0.093***
	(0.062)	(0.025)	(0.031)	(0.021)
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
Model	Tax Adj.	Call Adj.	No Call	Q4
Adj. R^2	0.715	0.563	0.568	0.582
N	75,759	76,522	47,103	27,461

We retest our baseline regression model in equation (1) with the following modifications: in column (1), we use the tax-adjusted yield spread as the dependent variable; in column (2), we use the call-adjusted yield spread as the dependent variable; in column (3), we instead exclude any issue with callable bonds; in column (4), we use a subsample of bonds issued in the last quarter of each year. Robust standard errors clustered by state and issuance year-month are reported in parentheses. The stars *, **, ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.3: Fire Prevention and Suppression Expenditures

	(1)	(2)	(3)	(4)	(5)	(6)
	Prevention/Acre		StateSuppr/Acre		FedSuppr/Acre	
$\mathbf{1}_{CA}$	-333.67***	-344.23***	8555.68***	30106.22***	287.86*	1514.87***
	(79.93)	(110.09)	(2380.79)	(7428.03)	(155.31)	(376.57)
N(Fires)		0.17		-121.66***		-7.89***
		(0.17)		(38.09)		(2.50)
$\mathbf{1}_{CA} \times N$(Fires)		-0.18		-0.61		0.82
		(0.17)		(2.08)		(1.75)
N(Str. Damaged)		0.00		-3.87**		0.80
		(0.01)		(1.65)		(0.49)
$\mathbf{1}_{CA} \times N$(Str. Dmg.)		-0.00		-1.55**		-1.01**
		(0.01)		(0.64)		(0.48)
Constant	365.25***	395.25***	679.98***	764.79***	324.67***	296.17***
	(79.89)	(109.63)	(130.06)	(205.55)	(78.83)	(110.90)
Adj. R^2	-0.001	-0.012	0.494	0.773	0.010	0.008
N	374	352	85	85	81	81

This table reports OLS estimates of the annual expenditure on fire prevention per acre (columns (1) and (2)), state expenditure on fire suppression per burned acre (columns (3) and (4)), and state-specific federal expenditure per burned acre as the dependent variable (columns (5) and (6)). 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. We obtain fire prevention data from the USDA Forest Service and fire suppression data from Cook and Becker (2017).