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

Luis A. Lopez, Dermot Murphy, Nitzan Tzur-Ilan, and Sean Wilkoff*

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ABSTRACT

Smoke from in-state and out-of-state wildfires is associated with higher borrowing costs in the healthcare industry, amounting to $270 million in incremental costs from 2010–2019. The effects are strongest in high-uninsurance counties, where wildfire smoke increases uncompensated care costs and reduces hospital profits. In California, wildfire prevention expenditures are lower and suppression expenditures are higher, suggesting policy is partially responsible for cross-state borrowing cost externalities. Migration sorting exacerbates the borrowing cost effects by concentrating vulnerable households in high-smoke counties. Our findings underline the importance of interstate coordination to prevent and suppress wildfires and provide guidance on cost-sharing between states.

JEL Classification: R31, O18, N32

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

*Luis A. Lopez (lal@uic.edu) and Dermot Murphy (murphyd@uic.edu) are with the College of Business at the University of Illinois Chicago, Nitzan Tzur-Ilan (Nitzan.TzurIlan@dal.frb.org) is with the Federal Reserve Bank of Dallas, and Sean Wilkoff (swilkoff@unr.edu) is with the College of Business at the University of Nevada, Reno. We thank Effi Benmelech, Dan Garrett, Gustavo Grullon, Christoph Herpfer, Matthew Kahn, Wen-Chi Liao, Brian McCartan, Gary Painter, Robert Parrino, Frederik Strabo, Fabrice Tourre, Tingyu Zhou, Qifei Zhu, and seminar and conference participants at the AREUEA 2025 National Conference, the Baruch/JFQA Climate Finance and Sustainability Conference, Chapman University, the Federal Reserve Bank of Chicago, the 2025 FIRS Conference, the 2024 FMA International Emerging Scholars Initiative, the pre-WFA Summer Real Estate Research Symposium, the University of Illinois Chicago, the University of Memphis, and the University of Texas at San Antonio for helpful comments. We thank Dylan Ryfe for excellent research assistance. We affirm that we have no material financial interests related to this research. The information presented herein is partially based on data from the FRBNY Consumer Credit Panel/Equifax (CCP) and the Federal Reserve. All calculations, findings, and assertions are those of the authors. The views expressed in this paper are solely those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Dallas or the Federal Reserve System.

I. Introduction

Hazardous smoke pollution from large-scale wildfires has become increasingly severe over the last several decades. In California alone, over 4.3 million acres were burned by wildfires in 2020, resulting in a 15-20% surge in hospitalizations due to exposure to toxic particulate matter ($PM_{2.5}$), which is deadly to vulnerable populations (Deryugina et al., 2019; McCormick, 2020). Municipalities outside burn regions are regularly exposed to traveling smoke plumes from distant wildfires. For example, Nevada has declared several air quality emergencies in response to California wildfires over the past decade. Recent estimates indicate that wildfire smoke pollution is responsible for about 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 this increased demand for healthcare services. $PM_{2.5}$ exposure is associated with increased emergency room (ER) visits for chronic conditions such as heart disease, asthma, and emphysema, and over seven million deaths per year (Heft-Neal et al., 2023). The increased demand can be profitable or unprofitable for the service provider, depending on the patient mix. The average profit margin for ER visits 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). Hospitals already operate on thin profit margins—if $PM_{2.5}$ exposure increases relative demand from underinsured patients in the long run, then hospitals may face solvency issues and lose access to capital markets, which in turn reduces quality of care and increases mortality rates (Aghamolla et al., 2024).

In this study, we examine the effect of wildfire smoke on credit risk for healthcare service providers. The healthcare municipal bond offering market provides an ideal laboratory for testing this effect 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, which in turn comprise about 70% of hospitals in the US, 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 an alarming 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 underlying drivers of hospital credit risk.

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

We find that wildfire smoke pollution ($Smoke$) is associated with significantly higher healthcare municipal borrowing costs. A one standard deviation increase in $Smoke$ is associated with a 7.1 basis point (bps) increase in the average offering yield spread for hospitals, and a 12.1 bps increase for nursing homes which also provide healthcare services for afflicted patients. These findings are robust to including county fixed effects, state-year fixed effects, and controls for direct physical damages from local wildfires. The yield effects correspond to $270 million in additional interest expenses for bonds issued in counties with above-mean

Smoke. Extrapolating from current smoke trends, we predict another \$650 million in interest expenses over the next ten years. These findings suggest that wildfire smoke pollution increases healthcare service demand that is unprofitable for service providers, thereby increasing their credit risk.

Out-of-state wildfire smoke is also associated with higher healthcare municipal borrowing costs. 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* effects on healthcare borrowing costs (5.8 bps for hospitals and 9.2 bps for nursing homes) are only slightly lower than the *HomeSmoke* effects (7.3 bps for hospitals and 14.6 bps for nursing homes). Wildfires in California increased *Smoke* in Nevada by 2.5 standard deviations in 2020—our point estimates suggest that an average \$90 million hospital issue in Nevada in 2020 would incur an additional \$1.3 million in interest expenses. These findings call for increased 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).

The *AwaySmoke* results suggest that reduced state-level investment in wildfire prevention imposes costly externalities on nearby states. For example, the California Council on Science and Technology (CCST) notes that its 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 largely institutional, in the sense that "institutional advancement for people [in the firefighting industry in California] has to do with how well you perform the firefighting mission, not how well you reduce firefighting hazard" (Boxall, 2020). Using data on wildfire prevention expenditures from the USDA Forest Service, we show that California spends about $334 less on wildfire prevention per acre, compared to an average of $365 per acre in the remaining states. These results suggest that institutional and political frictions increase wildfire risk and impose costly externalities on nearby states.

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

In response to escalating wildfire risk, economists emphasize the importance of "scaling up cost-effective investments in physical protection and addressing disparities in protection and postfire recovery for socially vulnerable populations" (Boomhower, 2023; Baylis and Boomhower, 2025). Wildfire smoke pollution may also disproportionately affect socially vulnerable populations with weak insurance coverage (Banzhaf, Ma and Timmins, 2019), thereby imposing additional financial stress on local healthcare providers. In cross-sectional tests, we find that the *Smoke* effects on healthcare yields are 66% to 75% larger in high-uninsurance counties. Hospital-level tests show that *Smoke* in high-uninsurance counties decreases profit margins by 0.53 percentage points (17% of the mean) and increases uncompensated care costs, i.e. non-payment from uninsured patients or insurance providers, by 0.13 percentage points (3% of the mean). These results suggest that wildfire smoke increases disparities in environmental protection for socially vulnerable populations.

Survey findings indicate that wildfire smoke is priced in the healthcare municipal bond market if local investors believe that wildfires will remain a permanent part of the landscape. Local investors are important for pricing local municipal bonds because the interest income on local bonds is typically state tax-deductible. Thus, their beliefs on climate change, which are correlated with beliefs on wildfire risk (Lacroix, Gifford and Rush, 2019), likely determine if wildfire smoke is priced in the local market. To test this channel, we obtain county-level survey data from Yale University on the percentage of adults who are worried about global warming or believe it will harm US residents (Howe et al., 2015; Marlon et al., 2022). We find that smoke-yield effects are strongest in counties where more residents believe global warming is worrisome or harmful.

Long-run concerns about wildfire smoke are also reflected in migration patterns. Using household data from the Federal Reserve Bank of New York (FRBNY) Equifax Consumer Credit Panel (CCP), a 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. The resulting patient composition thereby skews more toward Medicare-insured residents who are less likely to change addresses (Mateyka and He, 2022) and uninsured or Medicaid-insured residents who are more likely to have low credit scores, placing further stress on the finances of local healthcare providers.

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

II. Related Literature

Our study builds on the literature on climate finance. Edmans and Kacperczyk (2022) note that the financial costs associated with climate finance stem not only from technological, political, and policy uncertainty (e.g., Bolton and Kacperczyk, 2021), but also from physical damage risk. In support of this latter channel, recent studies 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).[1] We contribute to this literature by focusing on environmental health risks from wildfire smoke, which are distinct from physical damage risks from other climate events, and by highlighting the cost externalities for healthcare service providers.

Our study contributes to the literature on economic effects associated with air pollution or $PM_{2.5}$ exposure. Burke et al. (2021) show that wildfire smoke is eroding the success of the Clean Air Act in reducing air pollution, making it difficult for municipalities to meet the EPA's National Ambient Air Quality Standards (NAAQS). For NAAQS-incompliant counties, local municipal borrowing costs are higher due to regulatory uncertainty from the

[1] 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; Jerch, Kahn and Lin, 2023; Bakkensen, Phan and Wong, 2024).

EPA (Jha, Karolyi and Muller, 2020).[2] The healthcare industry is uniquely affected by wildfire smoke due to changes in service demand, and we provide new evidence that wildfire smoke is a costly externality that increases hospital borrowing costs, which in turn have been shown to reduce quality of care and increase hospital mortality rates (Aghamolla et al., 2024).

Our study contributes to the growing literature on the determinants of municipal borrowing costs. Local investors are typically important for pricing municipal bonds (Babina et al., 2021), and recent studies have shown that 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.[3]

Lastly, the financial health economics framework in Koijen, Philipson and Uhlig (2016) provides additional context for our findings. In their model, healthcare securities receive price discounts for two reasons: (1) a reduction in expected cash flows due to "disaster risk" from potential federal regulation that cuts healthcare reimbursements, and (2) a healthcare risk

[2] $PM_{2.5}$ exposure is also associated with reduced labor earnings (Isen, Rossin-Slater and Walker, 2017), employment and labor participation (Borgschulte, Molitor and Zou, 2022), and business activity (Addoum et al., 2023), and increased credit delinquencies (An, Gabriel and Tzur-Ilan, 2024).

[3] 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, despite the fact that female hospital CEOs earn lower salaries (Lewellen, 2025).

premium from a positive correlation between this disaster risk and tighter federal government budget constraints. In our setting, we provide evidence of a price discount on healthcare municipal bonds due to the "disaster risk" associated with wildfire smoke. As wildfire smoke tends to be localized to specific regions, the discount likely represents a reduction in expected cash flows, as local service providers have to absorb more unprofitable demand for healthcare services. However, part of this price discount may also reflect a wildfire smoke risk premium since the federal government is less likely to provide states with wildfire aid when it has tighter budget constraints.

III. Data

A. Municipal Bonds

We collect data on municipal bonds issued in 2010–2019 from the Mergent Municipal Bond Securities Database. For each bond, we collect its offering yield, use of proceeds code, number of years until maturity, bond size, credit ratings from Moody's and S&P (rated on a scale from 1 to 21, with higher numbers representing higher-quality credit ratings), and indicator variables for whether the bond is insured, general obligation, callable, and issued in the negotiated market. The use of proceeds code allows us to categorize bonds into three categories: (1) hospital bonds, (2) nursing home bonds, and (3) the remaining non-healthcare bonds. We also calculate the offering yield spread, a central outcome variable in our empirical analysis, by subtracting the coupon-equivalent risk-free rate from the offering yield.[4] Lastly, we aggregate our observations to the issue level: for issue size, we calculate

[4]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

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 American Community Survey (ACS). Following other municipal bond studies, we exclude outlier municipal bond records where (1) the maturity is over 100 years, (2) the offering yield exceeds 50 percentage points, (3) the coupon rate is variable or zero, (4) the issue is not exempt from federal taxes, (5) the bond was issued outside of the continental US, where wildfire smoke pollution information is not available.

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

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 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.[5]

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

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 during some years that double wildfire smoke pollution from previous years. Figures 2 and 3 illustrate the geographic variation in annual cumulative smoke exposure and smoke days over time. To get a sense of relative changes over time, the former variable is standardized by subtracting its mean from 2006–2009 and then dividing the difference by its standard deviation from 2006–2009. The figures indicate that wildfire smoke pollution was concentrated in the Midwest during the early part of the decade, but has since shifted to the Western US, with an exposure intensity spilling over to states in other regions.

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

IV. Wildfire Smoke and Healthcare Borrowing Costs

A. Baseline Analysis

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

Formally, we test the following baseline OLS regression model:

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

where $Hospital$ and $Nurse$ are indicator variables that equal one if the municipal bond issue is used to finance a hospital project and a nursing home project, respectively. The β^C coefficient measures the effect of *Smoke* on non-healthcare yield spreads, and the β^H and β^N coefficients measure the incremental effects of *Smoke* on hospital and nursing home yield spreads, respectively. The issue-level control variable vector X consists of the standalone $Hospital$ and $Nurse$ indicator variables, the natural logs of issue size and size-weighted number of years until maturity, indicator variables for whether the bond is callable, insured, general obligation, and issued in the negotiated market, and indicator variables for each credit rating and the unrated category.[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-year and county fixed effects. Standard errors are clustered by county and year-month of issuance.

[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; Cornaggia, Hund and Nguyen, 2022).

The results of this regression test are reported in Table III, column (1). We find that a one standard deviation increase in *Smoke* is associated with a 7.1 bps increase in the offering yield spread for hospitals, a 12.1 bps increase for nursing homes, and no change for non-healthcare issues. In column (2), we use industrial development bonds as our baseline instead of all non-healthcare bonds and find slightly stronger results (8.6 bps for hospitals and 13.3 bps for nursing homes). In columns (3) and (4), we use an alternative smoke measure (*SmokeDays*), calculated as the number of days in the year when wildfire smoke covered at least 75% of the census tracts in the county. This variable is also normalized by subtracting its mean of 38.9 days and 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 hospitals, the 7.1 bps effect represents 11.9% of one standard deviation in the offering yield spread (59.9 bps), 7.7% of the credit spread between Aaa and Baa1 bonds (92.8 bps), and $175 million in additional present value interest costs on the $24.7 billion worth of hospital municipal bonds issued in above-mean *Smoke* counties. For nursing homes, the 12.1 bps effect represents 20.2% of one standard deviation in the offering yield spread, 10.7% of the credit spread between Aaa and Baa1 bonds, and $95 million in additional present value interest costs on the $6 billion worth of nursing home municipal bonds issued in above-mean *Smoke* counties.[7] Extrapolating forward, if average annual exposure to wildfire smoke pollution were to increase again by 72 $\mu g/m^3$ over the next decade (66.1% of one standard deviation in our cumulative $PM_{2.5}$ exposure measure), then our point estimates suggest that repeat

[7]The present value interest costs are calculated using the duration approximation formula. For hospitals, $175 million = 0.00071 × 10 × $24.7 billion, where 10 years is the average duration for a hospital issue. For nursing homes, $95 million = 0.00121 × 13 × $6 billion, where 13 years is the average duration for a nursing home issue. For counties with above-mean *Smoke*, the average *Smoke* value is approximately one.

issues of hospital and nursing home municipal bonds from our main sample period would amount to another \$650 million in out-of-sample present value interest costs.[8]

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.

Additional 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, 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. Lastly, in Table A.2, we show that our baseline results are unaffected if we use the tax-adjusted yield spread as the dependent variable following Garrett et al. (2023), the call-adjusted yield spread as the dependent variable following Novy-Marx and Rauh (2012), the raw offering yield, or if we exclude callable issues from our baseline regression model.

[8] The present value interest cost is again calculated using the duration approximation formula: $0.661 \times 0.00071 \times 10 \times \$96$ billion $+ 0.661 \times 0.00121 \times 13 \times \$19$ billion, where \$96 billion and \$19 billion are the total issue sizes of hospital issues and nursing homes issues during our sample period, respectively.

B. 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:

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

where $F_{s,y}$ is a vector of in-state wildfire variables that includes the number of wildfires, the number of structures damaged, and the natural log of the number of burned acres in state s and year y.[9] To account for variation in state-level smoke predictability due to geographic factors such as weather, we interact the $F_{s,y}$ vector with state fixed effects (δ_s). The predicted component of wildfire smoke is attributable to in-state smoke ($HomeSmoke$), and the residual component is attributable to out-of-state smoke ($AwaySmoke$). For ease of interpretation, 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 IV. We find that $HomeSmoke$ and $AwaySmoke$ significantly increase hospital and nursing home borrowing costs. Specifically, a one standard deviation increase in $HomeSmoke$ is

[9] 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).

associated with a 7.3 bps increase in hospital borrowing costs and a 14.6 bps increase in nursing home borrowing costs, and a one standard deviation increase in *AwaySmoke* is associated with a 5.8 bps increase in hospital borrowing costs and a 9.2 bps increase in nursing home borrowing costs. In column (2), we 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 IV indicate that hospital borrowing costs would have increased by $5.8 \times 2.5 = 14.5$ bps as a result of the out-of-state smoke, while nursing home borrowing costs would have increased by $9.2 \times 2.5 = 23.0$ bps. For a hospital issue with an average size of $90 million and duration of ten years, the out-of-state smoke effect would increase total present value interest costs by $1.3 million. Similarly, for a nursing home issue with an average size of $30 million and duration of 13 years, the out-of-state smoke effect would increase total present value interest costs by about $0.9 million. Therefore, if Nevada were to build a hospital and a nursing home in 2020 and finance those investments using the municipal bond market, then wildfire smoke from California would increase the associated borrowing costs by $2.2 million.

C. Prevention, Suppression, and Externalities

Should we classify the *AwaySmoke* effects as cross-state negative externalities or 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 this section, we provide an analysis of prevention and suppression expenditures in California, where a large percentage of drifting wildfire smoke plumes currently originate in the US.

From a prevention perspective, related research supports the "externality" classification. In the case of California, the CCST notes that the state has a "long history of underinvestment in 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 that includes information on all activities and costs of hazardous fuel treatment reduction 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 V 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 actually spends more on wildfire suppression relative to other states, perhaps as a consequence of 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 (*StateExp/Acre*), and state-year federal expenditure on wildfire suppression per burned acre (*FedExp/Acre*). Our regression results in columns (3) and (4) of Table V indicate that California spends about $9,236 on wildfire suppression per burned acre, compared to an average of $680 per burned acre in the remaining states. 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 spending 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).

D. Socially Vulnerable Populations

As wildfire risk increases, economists emphasize the importance of "scaling up cost-effective investments in physical protection and addressing disparities in protection and post-fire recovery for socially vulnerable populations" (Boomhower, 2023; Baylis and Boomhower, 2025). In a similar vein, wildfire smoke pollution may also have a disproportionate effect on socially vulnerable populations (Banzhaf, Ma and Timmins, 2019). Wildfire smoke is more likely to impose greater financial stress on healthcare service providers operating in socially vulnerable areas because incoming patients are less likely to have complete insurance coverage.

We test the validity of this channel by exploiting cross-county variation in the share of the population that does not have health insurance. We collect insurance data from the US Census Bureau's ACS database. We calculate each county's mean uninsurance share and categorize each county as "high uninsurance" or "low uninsurance" if its mean share is above or below the median value across all counties (9.8%). We then retest the baseline regression model in equation (1) using a stratified sampling approach based on these two uninsurance categories. The subsample regression results are reported in columns (1) to (2) of Table VI. We find that the *Smoke* effect on hospital yields is about 66% larger in high-uninsurance counties compared to low-uninsurance counties (8.3 bps versus 5.0 bps) and that the *Smoke* effect on nursing home yields is about 75% larger in high-uninsurance counties (19.9 bps versus 9.9 bps).

Given our focus on socially vulnerable populations in this section, we also test the *Smoke* effects by minority share. In particular, we divide US counties into "high minority" or "low minority" using the median combined share of Black and Hispanic residents (16.7%). The results in columns (3) to (4) of Table VI indicate that the *Smoke* effects are largest in high minority counties. Our results suggest that wildfire smoke pollution disproportionately affects socially vulnerable populations by placing greater financial stress on local hospitals and nursing homes.[10]

[10]In Internet Appendix A and the associated Table A.3, we further show that the *Smoke* effects are strongest for hospitals and nursing homes that have weaker credit ratings and thus less capacity to provide uncompensated care for incoming patients with smoke-related illnesses.

E. Long-Run Beliefs about Wildfires

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

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

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

V. Long-Term Migration and Residential Sorting

Smoke-induced migration patterns could potentially exacerbate the healthcare borrowing cost effects documented in our baseline analysis. In a Rosen-Roback framework, which models the intercity equilibrium between wages and housing costs, increased exposure to smoke pollution acts as a negative amenity shock for local residents. 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, thereby generating worse profit margins for hospital ER departments (Wilson and Cutler, 2014). In this section, we examine the long-run impact of smoke pollution exposure on the county population stock and county population flow.

A. Population Stock

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

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

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

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

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

B. Population Flow

Skilled labor is correlated not only with age but also with other individual characteristics, such as credit score. In the next step of our migration analysis, we use the FRBNY Equifax Consumer Credit Panel (CCP) data set to explore the effect of smoke pollution on residential sorting and county population flow in the cross-section of age and credit score. The CCP data set is a 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, $OutMigration_i$ 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 IX and graphically in Figure 5. The strongest smoke effect on out-migration is concentrated 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% increase in out-migration over ten years. Statistically significant effects are also observed for individuals aged 40-65 in the highest or second-highest Equifax Risk Score groups (1.1% and 1.0%, respectively). These results indicate that wildfire smoke is more likely to drive away younger, productive residents with strong credit scores, skewing the patient composition toward the remaining age and credit score groups.[11] Since many older residents are Medicare-insured and many low-credit residents are uninsured or Medicaid-insured, hospitals in high-smoke areas are exposed to greater operational challenges through the migration channel in the long run.

[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.

VI. Real Investment and Profitability

In this last section, we analyze the effects of wildfire smoke pollution on real investment spending, profitability, and uncompensated care costs for hospitals. We first focus on investment spending. If wildfire smoke strains hospital financial resources and increases their cost of capital, hospitals may respond by reducing average investment activity and relying more on endowment returns to generate investment capital. On the latter point, Q-theory predicts that investment spending should only react to cash flow shocks in the presence of market frictions—in practice, the two most relevant frictions are agency conflicts and financial constraints (Stein, 2003). Adelino, Lewellen and Sundaram (2015) argue that for non-profit hospitals, investment sensitivity to cash flow shocks is attributable only to the latter, likely due to the sector's unique governance structure. Therefore, higher investment sensitivity to cash flow shocks can be interpreted as tighter financial constraints.

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

Formally, we test the following OLS regression model:

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

where $k \in \{1, 2\}$. The control variable vector $X_{h,j,t}$ from Adelino, Lewellen and Sundaram (2015) includes the following: $g(SRev)$, the percentage change in hospital net service revenue from $t-1$ to t; $OpInc$, the ratio of operating income in year t to net fixed assets in year $t-1$; $\log(TRev)$, the natural log of total revenue in year t; $FinInv$, the ratio of financial investment value to net fixed assets for the hospital in year $t-1$; and state-year and hospital fixed effects. As in Adelino, Lewellen and Sundaram (2015), we require hospitals to have at least \$1 million in assets and service revenue and truncate each variable at the top and bottom 1% of its distribution. The summary statistics in Table X indicate that the variable distributions are similar to those reported in Adelino, Lewellen and Sundaram (2015).

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

Hospital profitability may also be affected by *Smoke* if there is increased demand for healthcare services from uninsured or underinsured patients. To examine profitability, we focus on the one-year lead values of two key variables: (1) *Profit Margin*, calculated as the difference between total revenues and total costs, expressed as a percentage of total revenues, and (2) *% Uncomp. Care*, calculated as total uncompensated care costs as a percentage of total revenues. The latter variable is mainly attributable to non-payment from uninsured patients for healthcare services, and lower reimbursement rates from Medicaid or Medicare insurance providers.

Methodologically, we regress *Profit Margin* and *% Uncomp. Care* on *Smoke* and the set of control variables X from our previous tests in equation (6). The results are reported in Table XII. In columns (1) and (2), we focus on counties with an above-median uninsurance rate. In column (1), we find that a one standard deviation increase in *Smoke* is associated with a 0.53 percentage point decrease in the hospital profit margin or a 16.5% decrease in the average profit margin (3.22%). In column (2), we find that a one standard deviation increase in *Smoke* is associated with a 0.13 percentage point increase in uncompensated care costs or a 2.7% increase in the average uncompensated care cost (4.79%). By contrast, for the below-median uninsurance rate counties in columns (3) and (4), we find that *Smoke* has no statistically significant effects on profit margins or uncompensated care costs. Overall, these results indicate that *Smoke* is associated with higher uncompensated care costs and lower profit margins and counties where more residents lack health insurance.

Lastly, in Internet Appendix B, we provide supporting evidence that wildfire smoke is associated with increased respiratory illnesses and ER visits. We show that a one standard deviation increase in *Smoke* is associated with 8.8 additional asthma cases per 1,000 people and 2.4 additional ER visits per 1,000 people and that a one standard deviation increase in *AwaySmoke* is associated with similar effects. These results reflect findings in Qiu et al. (2025) that the US mortality rate from wildfire smoke is expected to double over the next several decades. Overall, these results further suggest that wildfire smoke pollution reduces profit margins and increases credit risk for hospitals, as older households and lower-income households are disproportionately affected by wildfire smoke pollution and generate negative profit margins for hospitals (Wilson and Cutler, 2014).

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 that are downwind of wildfires do not suffer from physical damage but do suffer the health and economic costs of poor air quality, even when the origin of the fire is in another state or country. In many regions, these costs are expected to increase as air quality deteriorates.

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 associated with significantly higher borrowing costs for hospitals and nursing homes. Specifically, a one standard deviation increase in smoke pollution exposure is associated with a 7.1 bps increase in offering yield spread for hospital issues, and a 12.1 bps increase for nursing home issues. In high-smoke counties, these effects translate to about $175 million in realized interest costs for hospital issues and $95 million for nursing home issues. The borrowing cost effects are strongest in counties with a high uninsurance rate, and supporting hospital-level tests indicate that smoke also significantly decreases profit margins and increases uncompensated care costs in these counties. Importantly, we document that out-of-state wildfire smoke significantly contributes to the borrowing costs effects, suggesting that poor wildfire management imposes costly externalities on other states. Indeed, we find evidence that California, a major source of drifting wildfire smoke for many states in recent years, spends less on wildfire prevention and more on wildfire suppression, relative to other states.

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

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

REFERENCES

Acharya, Viral V, Timothy Johnson, Suresh Sundaresan, and Tuomas Tomunen. 2022. "Is physical climate risk priced? Evidence from regional variation in exposure to heat stress." Working paper. National Bureau of Economic Research.

Addoum, Jawad M, Dimitrios Gounopoulos, Matthew Gustafson, Ryan Lewis, and Tam Nguyen. 2023. "Does Wildfire Smoke Choke Local Business?" Working paper. Cornell University.

Adelino, Manuel, Katharina Lewellen, and Anant Sundaram. 2015. "Investment decisions of nonprofit firms: Evidence from hospitals." *The Journal of Finance*, 70(4): 1583–1628.

Adelino, Manuel, Katharina Lewellen, and W Ben McCartney. 2022. "Hospital financial health and clinical choices: evidence from the financial crisis." *Management Science*, 68(3): 2098–2119.

Aghamolla, Cyrus, Jash Jain, and Richard T Thakor. 2023. "When private equity comes to town: The local economic consequences of rising healthcare costs." Working paper. Rice University.

Aghamolla, Cyrus, Jash Jain, and Richard T Thakor. 2025. "The (going) public option: Equity market financing in the hospital industry." Working paper. Rice University.

Aghamolla, Cyrus, Pinar Karaca-Mandic, Xuelin Li, and Richard T Thakor. 2024. "Merchants of death: The effect of credit supply shocks on hospital outcomes." *American Economic Review*, 114(11): 3623–3668.

AHA. 2017. "Support hospitals access to tax-exempt bond financing." American Hospital Association. Retrieved at: `https://www.aha.org/2017-12-06-support-hospitals-access-tax-exempt-bond-financing`.

AHA. 2025. "Fast facts on U.S. hospitals, 2025." American Hospital Association. Retrieved at: `https://www.aha.org/statistics/fast-facts-us-hospitals`.

Ambrose, Brent W, Matthew Gustafson, Maxence Valentin, and Zihan Ye. 2025. "Voter-induced municipal credit risk." *Management Science.*

An, Xudong, Stuart A Gabriel, and Nitzan Tzur-Ilan. 2024. "Extreme wildfires, distant air pollution, and household financial health." Working paper. Federal Reserve Bank of Philadelphia.

AP News. 2024. "What it means for the Supreme Court to block enforcement of the EPA's 'good neighbor' pollution rule." Retrieved at: `https://apnews.com/article/supreme-court-epa-good-neighbor-air-pollution-ea23421c78999293267339faf4453cdb`.

Auh, Jun Kyung, Jaewon Choi, Tatyana Deryugina, and Tim Park. 2022. "Natural disasters and municipal bonds." Working paper. National Bureau of Economic Research.

Babina, Tania, Chotibhak Jotikasthira, Christian Lundblad, and Tarun Ramadorai. 2021. "Heterogeneous taxes and limited risk sharing: Evidence from municipal bonds." *The Review of Financial Studies*, 34(1): 509–568.

Bakkensen, Laura A, and Lint Barrage. 2022. "Going underwater? Flood risk belief heterogeneity and coastal home price dynamics." *The Review of Financial Studies*, 35(8): 3666–3709.

Bakkensen, Laura, Toan Phan, and Russell Wong. 2024. "Leveraging the Disagreement on Climate Change: Theory and Evidence." Working paper. Federal Reserve Bank of Richmond.

Bakke, Tor-Erik, and Toni M Whited. 2012. "Threshold events and identification: A study of cash shortfalls." *The Journal of Finance*, 67(3): 1083–1111.

Baldauf, Markus, Lorenzo Garlappi, and Constantine Yannelis. 2020. "Does climate change affect real estate prices? Only if you believe in it." *The Review of Financial Studies*, 33(3): 1256–1295.

Banzhaf, Spencer, Lala Ma, and Christopher Timmins. 2019. "Environmental justice: The economics of race, place, and pollution." *Journal of Economic Perspectives*, 33(1): 185–208.

Baylis, Patrick W, and Judson Boomhower. 2025. "Mandated vs. voluntary adaptation to natural disasters: The case of US wildfires." Journal of Political Economy, forthcoming.

Bergstresser, Daniel, and Jeffrey Pontiff. 2013. "Investment taxation and portfolio performance." *Journal of Public Economics*, 97: 245–257.

Betermier, Sebastien, Sara B Holland, and Sean Wilkoff. 2024. "How Do Retiree Health Benefit Promises Affect Municipal Financing?" Working paper. McGill University.

Bolton, P., and M. Kacperczyk. 2021. "Do investors care about carbon risk?" *Journal of Financial Economics*, 142: 517–549.

Boomhower, J. 2023. "Adapting to growing wildfire property risk." *Nature*, 382: 638–641.

Borgschulte, Mark, David Molitor, and Eric Yongchen Zou. 2022. "Air pollution and the labor market: Evidence from wildfire smoke." *Review of Economics and Statistics*, 1–46.

Boxall, Bettina. 2020. "Billions of Dollars Spent on Fighting California Wildfires, but Little on Prevention." Los Angeles Times. Retrieved at: `https://www.latimes.com/environment/story/2020-12-23/billions-spent-fighting-california-wildfires-little-on-prevention`.

Burke, Marshall, Anne Driscoll, Sam Heft-Neal, Jiani Xue, Jennifer Burney, and Michael Wara. 2021. "The changing risk and burden of wildfire in the United States." *Proceedings of the National Academy of Sciences*, 118(2): e2011048118.

Butler, Alexander W, and Hanyi Yi. 2022. "Aging and public financing costs: Evidence from US municipal bond markets." *Journal of Public Economics*, 211: 1–18.

Childs, Marissa L, Jessica Li, Jeffrey Wen, Sam Heft-Neal, Anne Driscoll, Sherrie Wang, Carlos F Gould, Minghao Qiu, Jennifer Burney, and Marshall Burke. 2022. "Daily local-level estimates of ambient wildfire smoke PM2. 5 for the contiguous US." *Environmental Science & Technology*, 56(19): 13607–13621.

Cook, P. S., and D. R. Becker. 2017. "State Funding for Wildfire Suppression in the Western U.S." Technical Report. University of Idaho Policy and Analysis Group.

Cornaggia, Kimberly, John Hund, and Giang Nguyen. 2022. "Investor attention and municipal bond returns." *Journal of Financial Markets*, 60: 100738.

Cornaggia, Kimberly, John Hund, Giang Nguyen, and Zihan Ye. 2022. "Opioid crisis effects on municipal finance." *The Review of Financial Studies*, 35(4): 2019–2066.

Cornaggia, K., X. Li, and Z. Ye. 2024. "Financial effects of remote product delivery: Evidence from hospitals." *Review of Financial Studies*, 37: 2817–2854.

Dennin, L. R., D. Nock, N. Z. Muller, M. Akindele, and P. J. Adams. 2025. "Socially vulnerable communities face disproportionate exposure and susceptibility to U.S. wildfire and prescribed burn smoke." *Communications Earth & Environment*, 6: 1–19.

Deryugina, Tatyana, Garth Heutel, Nolan H Miller, David Molitor, and Julian Reif. 2019. "The mortality and medical costs of air pollution: Evidence from changes in wind direction." *American Economic Review*, 109(12): 4178–4219.

Edmans, A., and M. T. Kacperczyk. 2022. "Sustainable Finance." *Review of Finance*, 69: 1309–1313.

Eidenshink, Jeff, Brian Schwind, Ken Brewer, Zhi-Liang Zhu, Brad Quayle, and Stephen Howard. 2007. "A project for monitoring trends in burn severity." *Fire Ecology*, 3: 3–21.

Gao, Pengjie, Chang Lee, and Dermot Murphy. 2019. "Municipal borrowing costs and state policies for distressed municipalites." *Journal of Financial Economics*, 132(2): 404–426.

Garrett, D., A. Ordin, J. W. Roberts, and J. C. Suárez Serrato. 2023. "Tax advantages and imperfect competition in auctions for municipal bonds." *Review of Economic Studies*, 90: 815–851.

Glaeser, Edward L, and Joseph Gyourko. 2005. "Urban decline and durable housing." *Journal of Political Economy*, 113(2): 345–375.

Goldsmith-Pinkham, Paul, Matthew T Gustafson, Ryan C Lewis, and Michael Schwert. 2023. "Sea-level rise exposure and municipal bond yields." *The Review of Financial Studies*, 36(11): 4588–4635.

Gürkaynak, Refet S, Brian Sack, and Jonathan H Wright. 2007. "The US Treasury yield curve: 1961 to the present." *Journal of Monetary Economics*, 54(8): 2291–2304.

Heft-Neal, Sam, Carlos F Gould, Marissa L Childs, Mathew V Kiang, Kari C Nadeau, Mark Duggan, Eran Bendavid, and Marshall Burke. 2023. "Emergency department visits respond nonlinearly to wildfire smoke." *Proceedings of the National Academy of Sciences*, 120(39): e2302409120.

Howe, Peter D, Matto Mildenberger, Jennifer R Marlon, and Anthony Leiserowitz. 2015. "Geographic variation in opinions on climate change at state and local scales in the USA." *Nature Climate Change*, 5(6): 596–603.

IQAir. 2024. "Crop burning smoke: A global health threat." Retrieved at: `https://www.iqair.com/newsroom/crop-burning-smoke-global-health-threat`.

Isen, Adam, Maya Rossin-Slater, and W Reed Walker. 2017. "Every breath you take—every dollar you'll make: The long-term consequences of the clean air act of 1970." *Journal of Political Economy*, 125(3): 848–902.

Jeon, Woongchan, Lint Barrage, and Kieran James Walsh. 2024. "Pricing Climate Risks: Evidence from Wildfires and Municipal Bonds." Working paper. ETH Zurich.

Jerch, Rhiannon, Matthew E Kahn, and Gary C Lin. 2023. "Local public finance dynamics and hurricane shocks." *Journal of Urban Economics*, 134: 103516.

Jha, Akshaya, Stephen A Karolyi, and Nicholas Z Muller. 2020. "Polluting public funds: The effect of environmental regulation on municipal bonds." Working paper. National Bureau of Economic Research.

Kaufman, B. G., S. R. Thomas, R. K. Randolph, J. R. Perry, K. W. Thompson, G. M. Holmes, and G. H. Pink. 2016. "The rising rate of rural hospital closures." *The Journal of Rural Health*, 32: 35–43.

Koijen, R. K., T. J. Philipson, and H. Uhlig. 2016. "Financial Health Economics." *Econometrica*, 84: 195–242.

Lacroix, K., R. Gifford, and J. Rush. 2019. "Climate change beliefs shape the interpretation of forest fire events." *Climatic Change*, 159: 103–120.

Lewellen, K. 2025. "Women in charge: evidence from hospitals." *Journal of Finance*, 80: 2199–2253.

Liu, Tong. 2022. "Bargaining with private equity: Implications for hospital prices and patient welfare." Working paper. Massachusetts Institute of Technology.

Longstaff, Francis A, Sanjay Mithal, and Eric Neis. 2005. "Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market." *The Journal of Finance*, 60(5): 2213–2253.

Marlon, Jennifer R, Xinran Wang, Parrish Bergquist, Peter D Howe, Anthony Leiserowitz, Edward Maibach, Matto Mildenberger, and Seth Rosenthal. 2022. "Change in US state-level public opinion about climate change: 2008–2020." *Environmental Research Letters*, 17(12): 124046.

Mateyka, Peter J., and Wan He. 2022. "Domestic Migration of Older Americans: 2015–2019." U.S. Census Bureau Current Population Reports P23-218, Washington, D.C. Accessed on 2025-06-17.

McCormick, Erin. 2020. "Doctors Alarmed by Surge in Hospital Visits as Toxic Smoke Engulfs West Coast." The Guardian. Retrieved at: `https://www.theguardian.com/world/2020/sep/18/wildfire-smoke-health-effects-hospitals`.

Nguyen, D. D., S. Ongena, S. Qi, and V. Sila. 2022. "Climate Change Risk and the Cost of Mortgage Credit." *Review of Finance*, 26: 1509–1549.

Noah, Terry L, Cameron P Worden, Meghan E Rebuli, and Ilona Jaspers. 2023. "The effects of wildfire smoke on asthma and allergy." *Current Allergy and Asthma Reports*, 23(7): 375–387.

Novy-Marx, R., and J. D. Rauh. 2012. "Fiscal imbalances and borrowing costs: Evidence from state investment losses." *American Economic Journal: Economic Policy*, 4: 182–213.

Painter, Marcus. 2020. "An inconvenient cost: The effects of climate change on municipal bonds." *Journal of Financial Economics*, 135(2): 468–482.

Qiu, Minghao, Christopher W Callahan, Iván Higuera-Mendieta, Lisa Rennels, Bryan Parthum, Noah S. Diffenbaugh, and Marshall Burke. 2025. "Valuing Wildfire Smoke Related Mortality Benefits from Climate Mitigation." Working paper. National Bureau of Economic Research.

Roback, J. 1982. "Wages, rents, and the quality of life." *Journal of Political Economy*, 90(6): 1257–1278.

Rosen, S. 1979. "Wage-based indexes of urban quality of life." In Mieszkowski, P. and Straszheim, M., editors, *Current Issues in Economics*. Philadelphia.

St. Denis, Lise A, Karen C Short, Kathryn McConnell, Maxwell C Cook, Nathan P Mietkiewicz, Mollie Buckland, and Jennifer K Balch. 2023. "All-hazards dataset mined from the US National Incident Management System 1999–2020." *Scientific Data*, 10(1): 112.

Stein, Jeremy C. 2003. "Agency, information and corporate investment." *Handbook of the Economics of Finance*, 1: 111–165.

van Binsbergen, Jules, Joao F Cocco, Marco Grotteria, and S Lakshmi. 2024. "Environmental health risks, property values and neighborhood composition." Working paper. University of Pennsylvania.

Wara, M., J. Boomhower, K. Dargan, P. Larsen, M. Prunicki, and A. D. Syphard. 2020. "The costs of wildfire in California." Technical Report. Stanford University.

Wilgus, May-Lin, and Maryum Merchant. 2024. "Clearing the air: Understanding the impact of wildfire smoke on asthma and COPD." Vol. 12, 307, MDPI.

Wilson, Michael, and David Cutler. 2014. "Emergency department profits are likely to continue as the Affordable Care Act expands coverage." *Health Affairs*, 33(5): 792–799.

DATA REFERENCES

Childs, Marissa. Jessica Li, Jeffrey Wen, Sam Heft-Neal, Anne Driscoll, Sherrie Wang, Carlos Gould, Minghao Qiu, Jennifer Burney, and Marshall Burke (2024). "Daily smoke PM2.5 predictions from Jan 1, 2006 to Dec 31, 2020." *Daily local-level estimates of ambient wildfire smoke PM2.5 for the contiguous US*. https://doi.org/10.7910/DVN/DJVMTV.

FTSE Russell (2024). Mergent Municipal Bond Securities Database. https://www.lseg.com/en/ftse-russell/mergent (accessed January 30, 2024).

FRBNY Consumer Credit Panel/Equifax Data (CCP) (2024). Equifax credit reports, 2010-2019. https://www.newyorkfed.org/research/staff_reports/sr479.

Healthcare Cost Report Information System Database (2021). "HCRIS Hospitals." https://www.nber.org/research/data/hcris-hosp (accessed August 3, 2021).

Howe, Peter D, Matto Mildenberger, Jennifer R Marlon, and Anthony Leiserowitz (2015). "Geographic variation in opinions on climate change at state and local scales in the USA." Nature Climate Change, 5(6): 596-603. Yale Climate Opinion Maps 2023. https://climatecommunication.yale.edu/visualizations-data/ycom-us/ (accessed September 15, 2024).

St Denis, Lise A, Karen C Short, Kathryn McConnell, Maxwell C Cook, Nathan P Mietkiewicz, Mollie Buckland, and Jennifer K Balch (2023). "All-hazards dataset mined from the US National Incident Management System 1999-2020: ICS-209-PLUS dataset." https://doi.org/10.6084/m9.figshare.19858927.v3

U.S. Census Bureau (2023). American Community Survey: 5-Year Estimates, 2009-2013. https://api.census.gov/data/2013/acs/acs5 (accessed January 16, 2023).

U.S. Census Bureau (2023). American Community Survey: 5-Year Estimates, 2010-2014. https://api.census.gov/data/2014/acs/acs5 (accessed January 16, 2023).

U.S. Census Bureau (2023). American Community Survey: 5-Year Estimates, 2011-2015. https://api.census.gov/data/2015/acs/acs5 (accessed January 16, 2023).

U.S. Census Bureau (2023). American Community Survey: 5-Year Estimates, 2012-2016. https://api.census.gov/data/2016/acs/acs5 (accessed January 16, 2023).

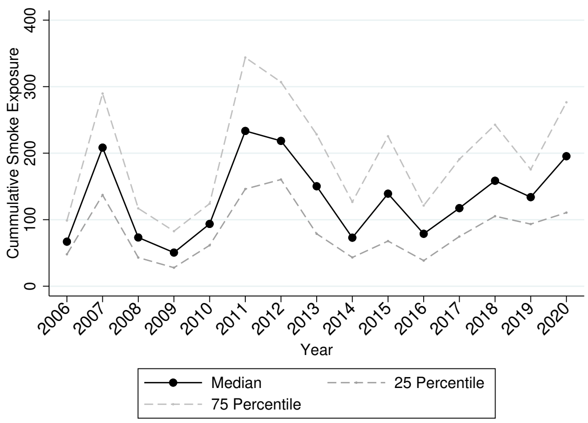
U.S. Census Bureau (2023). American Community Survey: 5-Year Estimates, 2013-2017. https://api.census.gov/data/2017/acs/acs5 (accessed January 16, 2023).

U.S. Census Bureau (2023). American Community Survey: 5-Year Estimates, 2014-2018. https://api.census.gov/data/2018/acs/acs5 (accessed January 16, 2023).

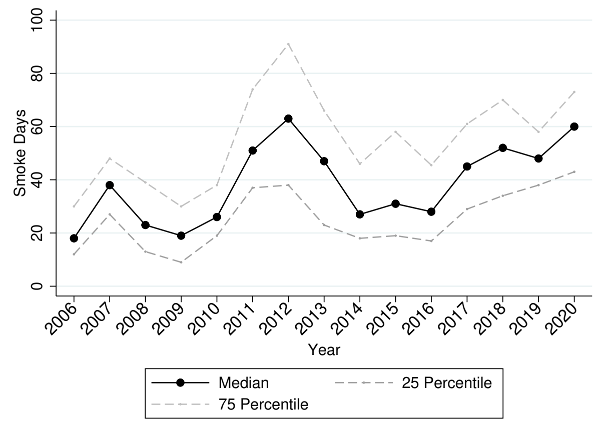
U.S. Census Bureau (2023). American Community Survey: 5-Year Estimates, 2015-2019. https://api.census.gov/data/2019/acs/acs5 (accessed January 16, 2023).

U.S. Census Bureau (2023). American Community Survey: 5-Year Estimates, 2016-2020. https://api.census.gov/data/2020/acs/acs5 (accessed January 16, 2023).

Health Forum, LLC (2024). 1999–2022 AHA Annual Survey. https://www.ahadata.com/aha-annual-survey-database



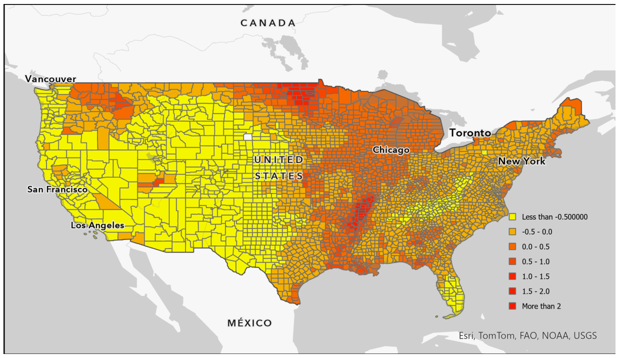
(a) Smoke Exposure



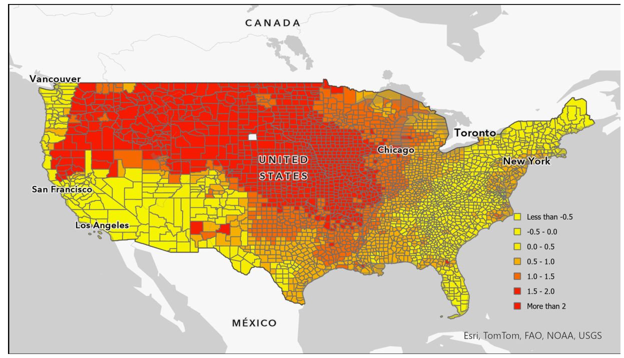
(b) Smoke Days

Figure 1. U.S. Wildfire Smoke by Year

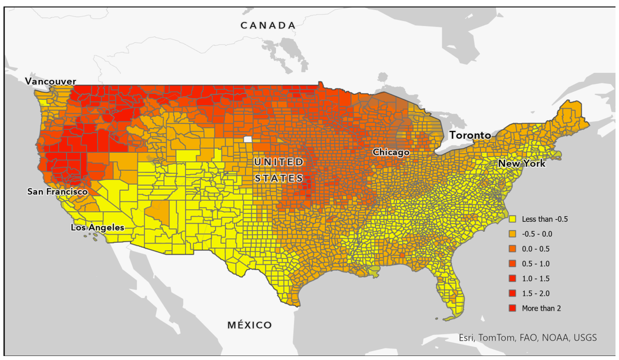
These figures provide time-series statistics on county-level cumulative wildfire smoke exposure and the number of smoke days from 2006 to 2020. Annual cumulative wildfire smoke exposure for each county is population-weighted at the census tract level. A smoke day occurs when more than 75% of the census 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).



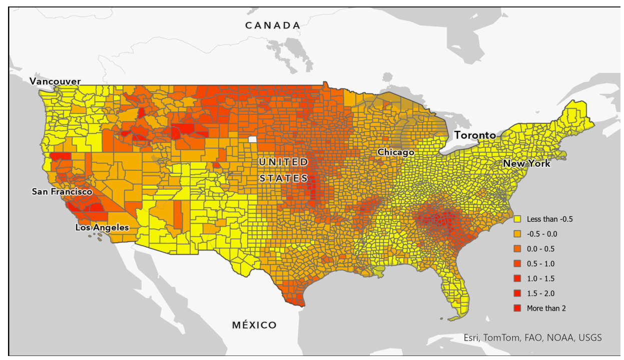
(a) 2010



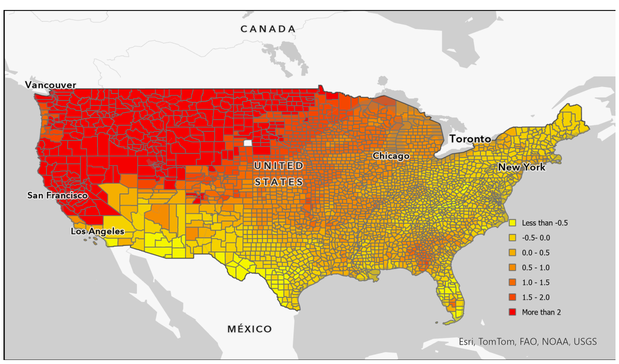
(b) 2012



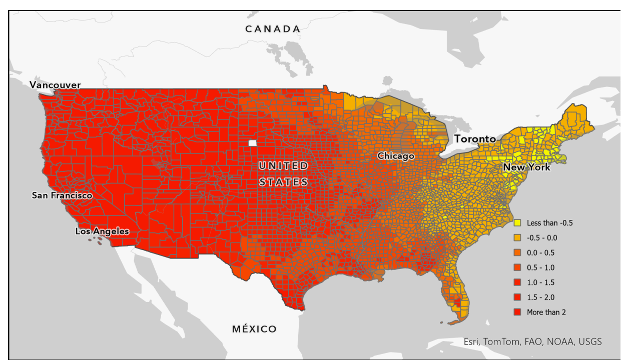
(c) 2014



(d) 2016



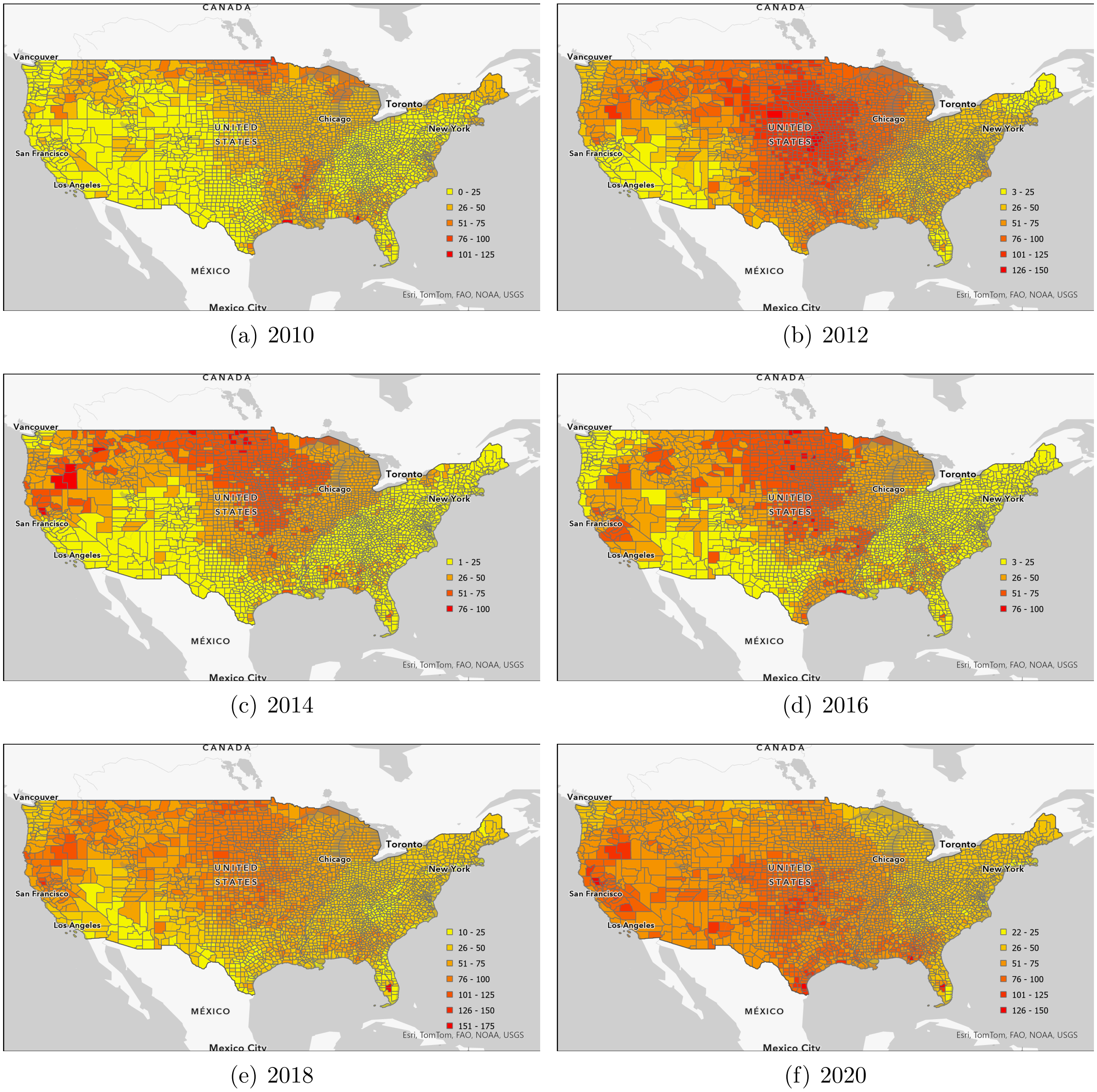
(e) 2018



(f) 2020

Figure 2. U.S. Wildfire Smoke Exposure

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



(a) 2010

(b) 2012

(c) 2014

(d) 2016

(e) 2018

(f) 2020

Figure 3. U.S. Wildfire Smoke Days

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

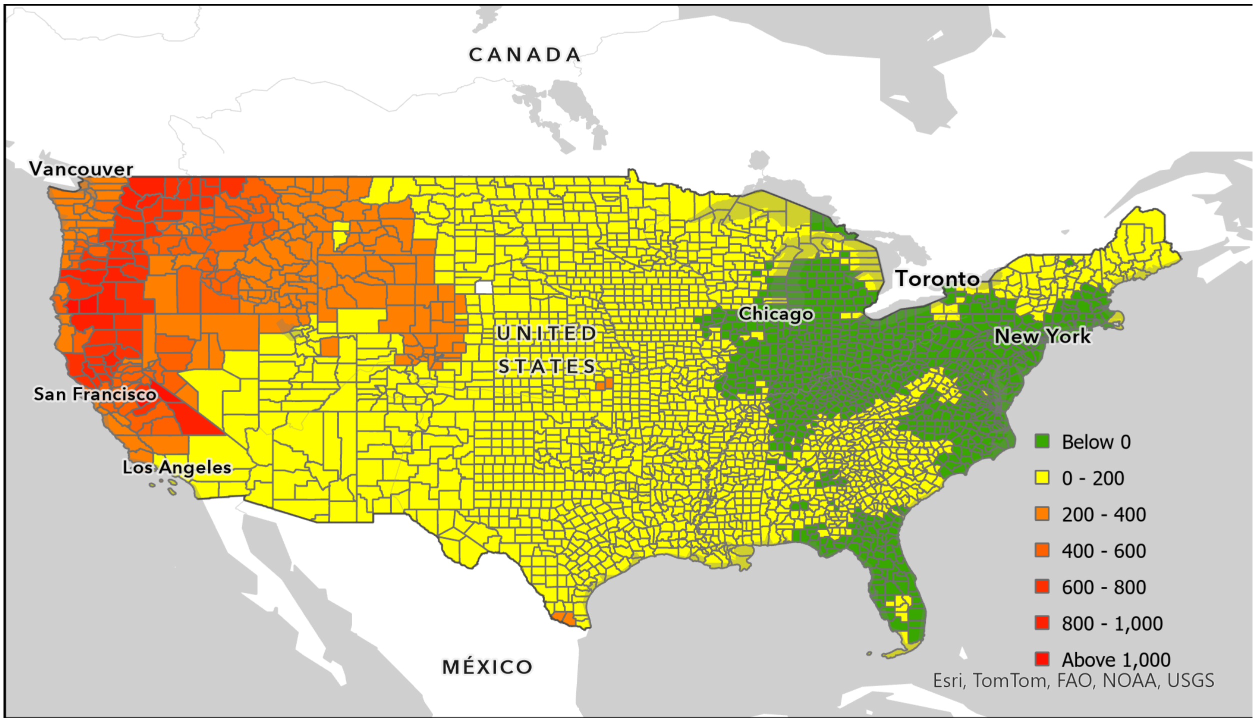


Figure 4. Decennial Change in Annual Cumulative Smoke Exposure

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

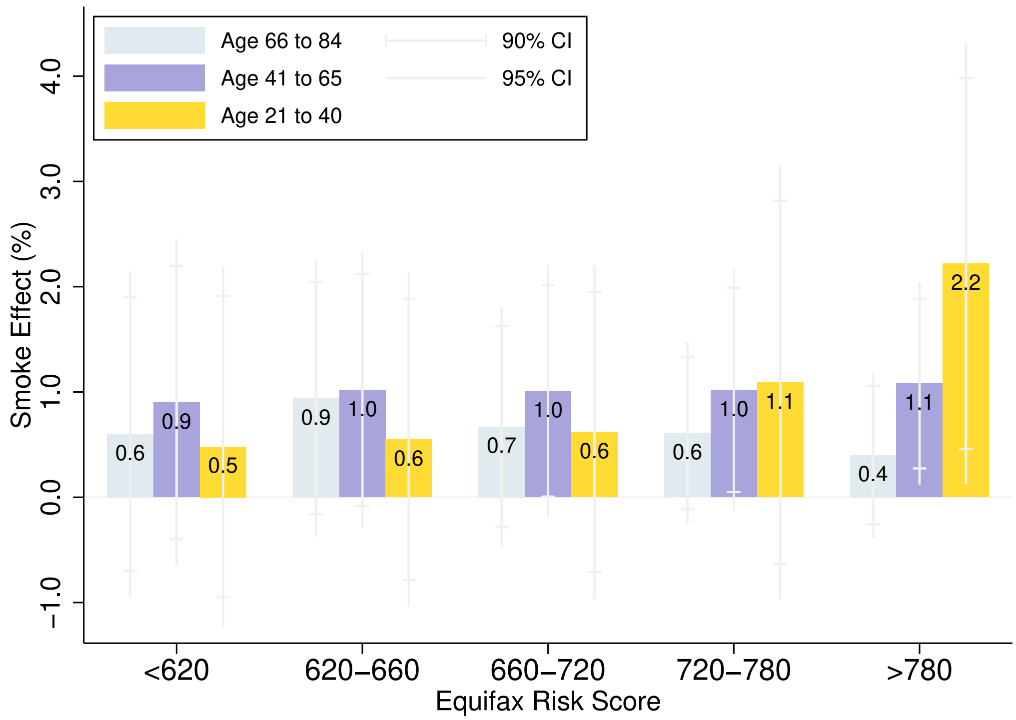


Figure 5. The Effects of Smoke Pollution on Out-Migration by Age and Credit Score

This figure reports linear probability model estimates of the effects of wildfire smoke pollution on out-migration for different subgroups based on information from the FRBNY Consumer Credit Panel (CCP)/Equifax data set. The dependent variable is $OutMigration$, an indicator variable that equals 1 if the individual in 2010 moved to a different county by 2019. The main independent variable is $SmokeChange$, calculated as 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: Non-Healthcare	Mean	Median	P25	P75	SD
Offering Yield Spread (%)	0.316	0.229	-0.021	0.557	0.578
Issue Size (M)	22.164	7.000	3.000	16.500	66.054
Years to Maturity	7.870	7.848	4.786	10.497	4.808
Rating Number	18.423	19.000	17.000	20.000	1.859
Unrated	0.265	0.000	0.000	1.000	0.441
General Obligation	0.673	1.000	0.000	1.000	0.469
Insured	0.145	0.000	0.000	0.000	0.352
Callable	0.714	1.000	0.000	1.000	0.452
Negotiated	0.301	0.000	0.000	1.000	0.459
Observations	76,075				

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

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

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

Table II: Wildfire Smoke Pollution Summary Statistics

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

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

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

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

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

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

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

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

Table V: Fire Prevention and Suppression Expenditures

	Fire Prevention		Fire Suppression			
	(1)	(2)	(3)	(4)	(5)	(6)
	Prevention/Acre		StateExp/Acre		FedExp/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 from the USDA Forest Service on activities and costs undertaken by the Forest Service on federal lands. Fire Suppression is from Cook and Becker (2017).

Table VI: Wildfire Smoke Pollution Effects by Uninsurance and Minority Shares

	(1) Yield Spread (%)	(2) Yield Spread (%)	(3) Yield Spread (%)	(4) Yield Spread (%)
$Smoke \times Hospital$	0.083***	0.050*	0.071***	0.044
	(0.024)	(0.029)	(0.023)	(0.029)
$Smoke \times Nurse$	0.207***	0.118**	0.235***	0.108*
	(0.060)	(0.049)	(0.060)	(0.057)
$Smoke$	0.007	0.001	0.009	0.006
	(0.007)	(0.008)	(0.008)	(0.007)
Controls	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Rating-Year FE	Yes	Yes	Yes	Yes
Insured-Year FE	Yes	Yes	Yes	Yes
Callable-Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Subsample	High Unins.	Low Unins.	High Minority	Low Minority
Adj. R^2	0.588	0.574	0.617	0.560
N	38,082	38,367	38,212	38,276

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

Table VII: Wildfire Smoke Pollution Effects by Climate Change Beliefs

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

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

Table VIII: The Effects of Smoke Pollution on Municipal Population

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

This table reports 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. $SmokeChange$ 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 IX: The Effects of Smoke Pollution on Out-Migration by Age and Credit Score

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

This table reports 15 separate linear probability model estimates of the effect of wildfire smoke pollution on out-migration. Each subgroup is based on individuals' Equifax Risk Score and Age. We use the FRBNY Consumer Credit Panel (CCP)/Equifax data set, which comprises 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. Robust standard errors clustered by county are reported in parentheses. The stars *, **, ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table X: Hospital Financial Summary Statistics

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

This table reports summary statistics for hospital financial variables from the HCRIS database. $g(NFA)_{t+1}$ and $g(NFA)_{t+2}$ are percentage change in hospital net fixed assets from year t to $t+1$ and $t+2$, respectively. $InvInc$ is the ratio of hospital investment income to the previous year's net fixed assets. $FinInv$ is the ratio of financial investment value to net fixed assets in the previous year. $g(SRev)$ is one-year growth in service revenue from year $t-1$ to t. $OpInc$ is the operating income ratio to the previous year's net fixed assets. Log $(TRev)$ is the natural log of total revenue. P25, P75, and SD are the 25th percentile cutoff, 75th percentile cutoff, and standard deviation of the distribution of that variable.

Table XI: The Effects of Smoke Pollution on Hospital Investment

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

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

Table XII: The Effects of Smoke Pollution on Hospital Profits

	(1) Profit Margin	(2) % Uncomp. Care	(3) Profit Margin	(4) % Uncomp. Care
Smoke	-0.533**	0.129*	-0.704	0.082
	(0.263)	(0.073)	(1.022)	(0.078)
$g(SRev)$	5.962***	-0.414	5.544	-0.157
	(1.313)	(0.447)	(5.429)	(0.378)
OpInc	0.320	0.157	4.825	-0.033
	(0.999)	(0.204)	(4.297)	(0.191)
$\log(TRev)$	-9.001***	-0.435	-39.536	1.497
	(2.741)	(0.583)	(37.961)	(1.616)
FinInv	-1.822***	-0.016	-0.944	0.137*
	(0.598)	(0.122)	(0.635)	(0.071)
Subsample	High Unins.	High Unins.	Low Unins.	Low Unins.
State-Year FE	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes
Adj. R^2	0.660	0.797	0.347	0.539
N	4,270	4,270	4,599	4,599

This table reports OLS estimates of the effect of smoke pollution on hospital profit margins and uncompensated care costs. Profit Margin is the difference between total hospital revenue and total hospital cost as a percentage of total hospital revenue. % Uncomp. Care is the total cost of uncompensated care as a percentage of total hospital revenue. In columns (1) and (2), we focus on counties with above-median uninsurance rates, and in columns (3) and (4), we focus on counties with below-median uninsurance rates. *Smoke* is the standardized population-weighted cumulative amount of smoke $PM_{2.5}$ exposure during the county-year. The remaining control variables are described in the main text. Robust standard errors clustered by hospital and fiscal end year-month are reported in parentheses. The stars *, **, ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

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

Luis A. Lopez, Dermot Murphy, Nitzan Tzur-Ilan, and Sean Wilkoff

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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."

*Luis A. Lopez (lal@uic.edu) and Dermot Murphy (murphyd@uic.edu) are with the College of Business at the University of Illinois Chicago, Nitzan Tzur-Ilan (Nitzan.TzurIlan@dal.frb.org) is with the Federal Reserve Bank of Dallas, and Sean Wilkoff (swilkoff@unr.edu) is with the College of Business at the University of Nevada, Reno. We thank Effi Benmelech, Dan Garrett, Gustavo Grullon, Christoph Herpfer, Matthew Kahn, Wen-Chi Liao, Brian McCartan, Gary Painter, Robert Parrino, Frederik Strabo, Fabrice Tourre, Tingyu Zhou, Qifei Zhu, and seminar and conference participants at the AREUEA 2025 National Conference, the Baruch/JFQA Climate Finance and Sustainability Conference, Chapman University, the Federal Reserve Bank of Chicago, the 2025 FIRS Conference, the 2024 FMA International Emerging Scholars Initiative, the pre-WFA Summer Real Estate Research Symposium, the University of Illinois Chicago, the University of Memphis, and the University of Texas at San Antonio for helpful comments. We thank Dylan Ryfe for excellent research assistance. We affirm that we have no material financial interests related to this research. The information presented herein is partially based on data from the FRBNY Consumer Credit Panel/Equifax (CCP) and the Federal Reserve. All calculations, findings, and assertions are those of the authors. The views expressed in this paper are solely those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Dallas or the Federal Reserve System.

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. 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. Lastly, in column (4), we use the raw offering yield and continue to find similar results.

Supporting cross-sectional tests further indicate that the baseline *Smoke* effects are strongest for hospitals and nursing homes that already have lower credit risk and thus less capacity to handle more patients with smoke-related illnesses. We divide our sample of healthcare issues into three groups: high quality (the top two credit rating categories), medium quality (the following two categories), and low quality (the remaining categories or unrated). Table A.3 reports the subsample regression results. We find the largest *Smoke* effects for low-quality hospitals (11.8 bps) and nursing homes (22.5 bps), a marginally statistically significant *Smoke* effect of 8.0 bps for medium-quality hospitals, and no effect for medium-quality nursing homes. We find a marginally statistically significant *Smoke* effect of -15.7 bps for high-quality hospitals, suggesting improved credit quality. One interpretation of this last finding is that hospitals with higher credit quality are more likely to receive patients with better insurance coverage.

Lastly, in Table A.4, we test how wildfire smoke pollution affects perceptions about climate change. First, we collect county-year survey data from Yale University on the percentage of adults worried about global warming or believing it will harm US residents. Second, we regress these percentages on our *Smoke* variable, county-year demographic control variables, and county and year fixed effects. The results in Table A.4 indicate that a one standard deviation increase in *Smoke* is associated with a 10 bps increase in the population share worried about global warming or believing it will be personally harmful. Columns (3) to (6) use *LagSmoke* and *LeadSmoke* as independent variables instead. The associated results show that *LagSmoke* increases harm perceptions, while *LeadSmoke* does not affect contemporaneous worry or harm perceptions, supporting the assertion in Borgschulte, Molitor and Zou (2022) that *Smoke* is quasi-randomly assigned. Overall, these results suggest that wildfire smoke affects long-run perceptions about future climate events.

Appendix A.2. Hospital Intake

In this Appendix, we show that wildfire smoke is associated with a significant increase in asthma cases, hospital ER visits, and hospital admissions. Previous research has shown that older and lower-income households are disproportionately affected by wildfire smoke pollution, generating negative profit margins for hospital ER departments (Wilson and Cutler, 2014). Combined with this previous research, our results further suggest that wildfire smoke reduces hospital profit margins, thereby increasing their credit risk.

Appendix A.2.1. Asthma Cases

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

We regress the number of asthma cases on our *Smoke* variable and include the control variable vector Z from our baseline regression in the main text, in addition to state and year fixed effects. The results in Table A.5 indicate that adults are more likely to receive an asthma diagnosis during years with high levels of wildfire smoke pollution, which is consistent with findings in Noah et al. (2023) and Wilgus and Merchant (2024). In particular, column (1) indicates that a one standard deviation increase in *Smoke* is associated with approximately nine additional asthma cases per 1,000 people annually. When we replace the state fixed effects with county fixed effects in column (2), the effect is slightly larger, with a point estimate of approximately 10 additional asthma cases per 1,000 people annually. Lastly, in column (3), we replace *Smoke* with *HomeSmoke* and *AwaySmoke*, and find that both measures are associated with a significant increase in asthma cases. Therefore, out-of-state wildfire smoke imposes negative health externalities on nearby states, and the negative financial externalities are highlighted in the main text.

Appendix A.2.2. Hospital ER Visits and Admissions

The increase in respiratory problems from wildfire smoke $PM_{2.5}$ exposure is likely associated with an increase in costly hospital ER visits. To explore this idea, we collect annual state-level data on total emergency room visits and hospital admissions from the Kaiser Family Foundation (KFF), a non-profit organization for health policy research, and the American Hospital Association. We regress the number of ER visits per 1,000 people on *Smoke* and include the same controls from our asthma tests. The results in Table A.6, column (1) indicate that a one standard deviation increase in *Smoke* is associated with approximately 2.5 additional ER visits per 1,000 people annually.

In column (2) of Table A.6, we retest the same regression, except that we replace *Smoke* with *HomeSmoke* and *AwaySmoke*. In this case, both measures are associated with significantly more ER visits (1.7 per 1,000 people and 2.2 per 1,000 people, respectively), indicating that out-of-state smoke also imposes real health externalities on neighboring states. Lastly, we repeat the tests in columns (1) and (2), except we use hospital admissions per 1,000 people as the dependent variable. The results in columns (3) and (4) indicate that hospital admissions similarly increase in response to greater in-state or out-of-state wildfire smoke levels.

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

Table A.1: Robustness Tests for Baseline Regressions

	(1) Yield Spread (%)	(2) Yield Spread (%)	(3) Yield Spread (%)	(4) Yield Spread (%)
Smoke	0.008	0.008	0.002	0.008
	(0.005)	(0.006)	(0.006)	(0.006)
Smoke × *Hospital*	0.070***	0.070***	0.073***	0.080***
	(0.021)	(0.020)	(0.022)	(0.021)
Smoke × *Nurse*	0.094**	0.115***	0.121***	0.113***
	(0.040)	(0.037)	(0.038)	(0.038)
LagSmoke	0.006			
	(0.006)			
LagSmoke × *Hospital*	-0.006			
	(0.021)			
LagSmoke × *Nurse*	-0.011			
	(0.044)			
LeadSmoke	0.001			
	(0.004)			
LeadSmoke × *Hospital*	0.005			
	(0.015)			
LeadSmoke × *Nurse*	0.066			
	(0.041)			
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	0.584	0.584	0.582	0.579
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 *Hospital* and *Nurse*; 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 county 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_{ijt} (Tax Adj.)	(2) y_{ijt} (Call Adj.)	(3) y_{ijt} (No Call)	(4) y_{ijt} (Raw)
Smoke	0.021^{**}	0.009	0.002	0.018^{**}
	(0.011)	(0.006)	(0.006)	(0.008)
$Smoke \times Hospital$	0.101^{***}	0.060^{***}	0.072^{***}	0.058^{***}
	(0.034)	(0.020)	(0.024)	(0.022)
$Smoke \times Nurse$	0.305^{***}	0.088^{**}	0.106^{*}	0.148^{***}
	(0.072)	(0.038)	(0.063)	(0.045)
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	Raw Yield
Adj. R^2	0.716	0.565	0.570	0.792
N	75,759	76,522	47,103	75,759

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 the raw yield as the dependent variable. 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 A.3: Wildfire Smoke Pollution Effects by Bond Quality

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

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

Table A.4: The Effects of Smoke Pollution on Yale Climate Opinions

	(1) %Worried	(2) %HarmUs	(3) %Worried	(4) %HarmUs	(5) %Worried	(6) %HarmUs
Smoke	0.105***	0.105***				
	(0.018)	(0.013)				
LagSmoke			-0.042	0.088***		
			(0.028)	(0.023)		
LeadSmoke					-0.028	0.000
					(0.019)	(0.017)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Demo. Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.879	0.889	0.879	0.889	0.879	0.889
N	12,424	12,424	12,424	12,424	12,424	12,424

This table reports ordinary least squares estimates of the effect of smoke pollution on climate opinions. The dependent variables are the county population share worried about climate change ("%Worried") or believes climate change will lead to harm ("%HarmUs"), as percentage points. *Smoke* is the standardized population-weighted cumulative amount of smoke $PM_{2.5}$ exposure during the county-year. *LagSmoke* is one-year lagged value of *Smoke*, while *LeadSmoke* is the one-year lead value of *Smoke*. The county-year demographic control variables are average home value, average rent, average household income, renter-to-owner ratio, elderly population share, Hispanic population share, and Black population share. Robust standard errors clustered by county are reported in parentheses. The stars *, **, ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.5: The Effects of Smoke Pollution on Asthma Cases

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

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

Table A.6: The Effects of Smoke Pollution on Hospital Utilization

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

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