



Federal Reserve
Bank of Dallas

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

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

Working Paper 2503 January 2025 (Revised October 2026)

Research Department

<https://doi.org/10.24149/wp2503r1>

Working papers from the Federal Reserve Bank of Dallas are preliminary drafts circulated for professional comment. The views in this paper are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Dallas or the Federal Reserve System. Any errors or omissions are the responsibility of the authors.

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

Luis A. Lopez[†], Dermot Murphy[‡], Nitzan Tzur-Ilan[§] and Sean Wilkoff[‡]

First Draft: August 31, 2024
Current Draft: August 31, 2026

Abstract

Climate risk pricing is not necessarily tied to physical damages from local climate events. Large-scale wildfires generate hazardous smoke plumes that impose costs on distant hospitals by increasing relative demand from underinsured patients. We show that wildfire smoke increases credit risk in the healthcare municipal bond market, especially in areas with high underinsurance. A natural experiment using the staggered expansion of Medicaid provides additional evidence consistent with the underinsurance channel. Hospital-level tests indicate that wildfire smoke reduces profitability and investment growth. Out-of-state wildfire smoke similarly increases healthcare credit risk, indicating that unchecked wildfires impose negative externalities on other states.

JEL Classification: R31, O18, H74, I11, Q54

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

* We thank Manuel Adelino, Effi Benmelech, Stephen Billings, Dan Garrett, Gustavo Grullon, Christoph Herpfer, Matthew Kahn, Wen-Chi Liao, Brian McCartan, Gary Painter, Robert Parrino, Adam Sacarny, Frederik Strabo, Fabrice Tourre, Sheng-Jun Xu, Tingyu Zhou, Qifei Zhu, and seminar and conference participants at the AREUEA 2025 National Conference, the Baruch/JFQA Climate Finance and Sustainability Conference, the 14th Annual Brookings Municipal Finance Conference, Chapman University, Dalhousie University, the Federal Reserve Bank of Chicago, the 2025 FIRS Conference, the 2024 FMA International Emerging Scholars Initiative, the 2025 NFA Conference, the 2025 pre-WFA Summer Real Estate Research Symposium, the University of Cincinnati, the University of Illinois Chicago, the University of Memphis, the University of Texas at San Antonio, the Yale Municipal Research Conference, Villanova University, 20th North American Meeting of the Urban Economics Association, and the University of Wisconsin–Madison for helpful comments. We thank Dylan Ryfe for excellent research assistance. We affirm that we have no material financial interests related to this research. 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.

[†]Luis A. Lopez, College of Business, University of Illinois Chicago, lal@uic.edu.

[‡]Dermot Murphy, College of Business, University of Illinois Chicago, murphyd@uic.edu.

[§]Nitzan Tzur-Ilan, Federal Reserve Bank of Dallas, Nitzan.TzurIlan@dal.frb.org, telephone: (773) 964-3936.

[‡]Sean Wilkoff, College of Business, University of Nevada Reno, swilkoff@unr.edu.

I. Introduction

The proliferation of wildfires around the globe has significantly reshaped economic and public health outcomes. In California alone, over 4.3 million acres were burned by wildfires in 2020, resulting in \$19 billion in economic losses and a 15-20% surge in hospitalizations (Safford et al., 2022; McCormick, 2020). Climate experts project that the likelihood of catastrophic wildfires will increase by another 50% over the next 75 years (UNEP, 2022), raising concerns about continued economic and public health effects.

The adverse consequences of wildfires are far-reaching and not confined to the immediate burn zones. Wildfires produce drifting smoke plumes that travel hundreds of miles and increase the volume of airborne toxic particulate matter (e.g., $\text{PM}_{2.5}$; Childs et al., 2022), which is causally associated with more emergency room (ER) visits, premature deaths, and admissions for heart disease, asthma, and emphysema (Deryugina et al., 2019; Heft-Neal et al., 2023). Wildfire smoke pollution is now responsible for about 20% of global $\text{PM}_{2.5}$ exposure, and almost 50% of $\text{PM}_{2.5}$ exposure in the Western US (UNEP, 2022). Anecdotally, large-scale wildfires in California have caused Nevada and Oregon to declare multiple air quality emergencies or alerts. Meanwhile, large-scale wildfires in Canada and the Northern US produce smoke plumes that decrease air quality in nearby US states (New York Times, 2026), imposing billions of dollars of adverse health damages (Bloomberg, 2025).

Hospitals have naturally absorbed much of the increased demand for healthcare services. However, the financial consequences are not immediately clear because the incremental demand can be profitable or unprofitable, and hospitals cannot perfectly ration services and accept only profitable patients.¹ Guided by the financial health economics framework in

¹Privately-insured patients generate high profit margins, while Medicare-insured, Medicaid-insured, and uninsured patients generate lower or even negative profit margins (Wilson and Cutler, 2014). While hospitals can ration services to some extent, federal laws prohibit U.S. hospitals from turning away underinsured

Koijen, Philipson and Uhlig (2016), we are the first to quantify how wildfire smoke, and not physical damages from the wildfires themselves or other natural disasters, uniquely affects the cost of capital, investment, and profitability in the healthcare industry. This is crucial because restricted access to capital markets is associated with reduced quality of care and increased mortality rates (Aghamolla et al., 2024). Furthermore, because of the long-distance nature of wildfire smoke, our study addresses an equally important and broad research question on whether climate pricing is bounded by local property damage or also reflects broader externalities.

The healthcare municipal bond market provides an ideal laboratory for testing the effect of wildfire smoke on the healthcare cost of capital because the borrowing costs (yields) are forward-looking and incorporate long-term expectations on issuer solvency. This market also represents a primary source of financing for non-profit hospitals (70% of US hospitals), and the offering yields translate to direct costs for the issuer and indirect costs for the patient (AHA, 2017, 2025). With hospitals closing at a higher rate in recent years, particularly in rural areas (Kaufman et al., 2016; Cornaggia, Li and Ye, 2024), it is more important than ever to understand the drivers of credit risk and investment.

Our analysis employs a continuous treatment design using *Smoke* as our “dosage” variable in a natural experiment setup (e.g., Callaway, Goodman-Bacon and Sant’Anna, 2024, 2026). *Smoke* is a standardized measure of exposure based on a novel panel of wildfire smoke data from the Stanford Echo Lab. Our identification strategy in the offering market relies on variation from two sources: (i) differences between healthcare and non-healthcare municipal bonds that are treated to a similar dosage of *Smoke*, and (ii) differences between two otherwise similar healthcare municipal bonds with different *Smoke* exposures. Our identifi-

patients in need of emergency medical treatment without providing, at a minimum, medical screening, stabilization, or proper transfer (U.S. Dept. of Health and Human Services, 2024).

cation strategy in the secondary market relies on within-bond yield changes in the healthcare market relative to the non-healthcare market following a dosage of *Smoke*.

We find that wildfire smoke pollution is associated with a significantly higher cost of capital for healthcare borrowers. A one standard deviation increase in *Smoke* is associated with a 6.7 basis point (bps) increase in the average offering yield spread for healthcare municipal bonds relative to non-healthcare municipal bonds. This yield change corresponds to \$170 million in present value interest costs on the \$25.4 billion of healthcare municipal bonds from above-mean *Smoke* counties, and another \$509 million in out-of-sample present-value interest costs over the next decade based on current smoke trends. A back-of-the-envelope calculation based on structural estimates from Goldsmith-Pinkham et al. (2023) indicates that the 6.7 bps yield effect corresponds to a 2.5% to 7.5% decrease in hospital asset value, a 2.0% to 4.0% increase in hospital asset volatility, or a combination of the two effects. Our findings are robust to the inclusion of State $\times$ Year-Month or County $\times$ Year-Month fixed effects, controls for direct physical damages from local wildfires, the exclusion of county-years where a wildfire is observed in the data, and the exclusion of California, where many wildfires occur during our sample period. We obtain similar point estimates if we focus on within-bond yield changes using secondary market yield spreads and bond fixed effects. Using the dynamic *Smoke* model in Borgschulte, Molitor and Zou (2022), we further find only contemporaneous *Smoke* matters for secondary yields, thereby indicating that innovations to *Smoke* are efficiently priced in the healthcare market.

The effect of *Smoke* on healthcare borrowing costs is more pronounced in counties with a greater number of underinsured residents per hospital (*Underins/Hosp*). Using insurance information from the US Census American Community Survey (ACS), we define individuals as underinsured if they are uninsured, Medicaid-insured, or Medicare-insured; these groups

are associated with negative hospital profit margins. We find that the effect of *Smoke* on healthcare borrowing costs is 55% stronger if *Underins/Hosp* is one standard deviation above its mean. By contrast, non-healthcare borrowing costs are unaffected by *Smoke* or its interaction with *Underins/Hosp*. These findings support our proposed mechanism whereby *Smoke* increases healthcare credit risk through the service demand channel.

Although we cannot randomly assign the population of underinsured residents, the staggered state-level expansion of Medicaid eligibility sharpens identification of the underinsurance channel. Following the passage of the Affordable Care Act (ACA) in 2010, the Supreme Court ruled that states could not be required to expand Medicaid eligibility under the ACA. Forty states have expanded Medicaid at different times since that ruling in June 2012, and a large share of uninsured residents in those states now have health insurance through the Medicaid program (Gao, Lee and Murphy, 2022). Overall hospital profitability from the underinsured category improved due to the expanded coverage. Importantly, we find that the incremental effect of *Smoke* on healthcare yields in high-underinsurance counties is attenuated after the state expands Medicaid eligibility relative to states that have not expanded it, further supporting the service demand channel.

Smoke also increases borrowing costs for hospitals in nearby states. Using wildfire data from the US Department of Homeland Security (DHS), we decompose *Smoke* into its in-state and out-of-state components (*HomeSmoke* and *AwaySmoke*). We find that the *AwaySmoke* effect on healthcare borrowing costs (7.3 bps) is statistically similar to the *HomeSmoke* effect (10.6 bps), indicating that wildfire smoke from other states is an important driver of healthcare credit risk. Reflecting our earlier evidence, we also observe that the effects of *HomeSmoke* and *AwaySmoke* on healthcare borrowing costs are significantly stronger in high-underinsurance counties. In general, these results indicate that climate pric-

ing is not necessarily influenced by property damage, since *Smoke* imposes negative external costs on areas that are not exposed to property damage risk. Furthermore, the *AwaySmoke* findings underline the importance of interstate coordination to tackle the growing economic and health issues surrounding wildfires, similar to how the “Good Neighbor” provision of the Clean Air Act was meant to regulate interstate industrial pollution before being blocked by the Supreme Court in 2024 (AP News, 2024).²

A systematic analysis of ER visits further indicates that *Smoke* constitutes a unique risk for healthcare service providers. Using ER data from the Agency for Healthcare Research and Quality (AHRQ), we find that a one standard deviation increase in *Smoke* is associated with a 0.8% increase in ER visits from underinsured residents, and a similar 0.8% increase in ER visits from privately insured patients. Because discharges from underinsured patients outnumber those from privately insured patients by approximately three-to-one, these percentage effects translate into a sizable increase in the number of underinsured patients relative to privately insured patients. The asymmetric effect translates into financial losses for *Smoke*-affected hospitals since ERs deliver about 50% of all medical care and underinsured patients generate negative profit margins (Wilson and Cutler, 2014).

An analysis of hospital profit margins and investment growth, based on data from the Healthcare Cost Report Information System (HCRIS) database, provides further support for our earlier tests and the proposed mechanism. In our last set of tests, we regress hospital profit margin and fixed asset growth on *Smoke* and its interaction with *Underins/Hosp*. In these regressions, we also include hospital fixed effects, State $\times$ Year fixed effects, and the

²Supporting tests show that fire suppression expenditures per acre are significantly higher in California than in nearby states, while fire prevention expenditures are significantly lower. Related research finds that California has a “long history of underinvestment in prevention and mitigation” due to institutional and political frictions (Wara et al., 2020; Boxall, 2020), suggesting that the *AwaySmoke* borrowing cost externalities in Western states are partially attributable to these frictions.

time-varying hospital-level controls from Adelino, Lewellen and Sundaram (2015). First, we find that *Smoke* is associated with significantly lower profit margins, particularly in high-underinsurance counties. The point estimates indicate that a one standard deviation increase in *Smoke* is associated with a 2.4% reduction in the average profit margin if *Underins/Hosp* is also one standard deviation above its mean. Second, we find that *Smoke* is also associated with a 4.8 percentage point reduction in hospital investment growth over the two-year horizon, which is consistent with the finding in Adelino, Cunha and Ferreira (2017) that higher borrowing costs are causally associated with reduced investment activity. Overall, the results from these hospital-level tests indicate that the adverse financial effects from *Smoke*-driven demand shocks translate to adverse real effects in the form of reduced investment.

Our study builds on the literature on climate finance. Recent studies have shown that long-term municipal bond yields are affected by exposure to physical climate risks stemming from rising sea levels (Painter, 2020; Goldsmith-Pinkham et al., 2023), heat stress (Acharya et al., 2022), or direct wildfire damages (Jeon, Barrage and Walsh, 2025). Additional studies focus on the perceived risk of physical property damage (e.g., Baldauf, Garlappi and Yanelis, 2020; Auh et al., 2022; Bakkensen and Barrage, 2022; Nguyen et al., 2022; Sautner et al., 2023; Jerch, Kahn and Lin, 2023; Bakkensen, Phan and Wong, 2025; Issler et al., 2024; Cookson, Gallagher and Mulder, 2026*a,b*), or perceived cancer risk from toxic plants and its effect on local real estate prices (van Binsbergen et al., 2026). In contrast, wildfire smoke introduces a novel form of climate risk because it affects populations far from the wildfires themselves, and does not damage the physical capital that forms the local tax base. By focusing on wildfire smoke exposure and comparing the yields of healthcare versus non-healthcare bonds in the same county, we can isolate climate risk from other confounding events that commonly accompany disaster events (e.g., emergency financial relief,

population or employment displacement, changes in local tax revenues, and damage to local infrastructure). Furthermore, given the long-distance nature of wildfire smoke, our results demonstrate that climate risk pricing is not necessarily tied solely to physical damage from local climate events.³

Our study also contributes to the growing literature on the determinants of municipal borrowing costs. Local investors are important for pricing municipal bonds (Babina et al., 2021), and the associated borrowing costs are influenced by a variety of local factors such as state taxes (Garrett et al., 2023; Ambrose et al., 2025), pension underfunding (Novy-Marx and Rauh, 2012; Betermier, Holland and Wilkoff, 2024), remote product delivery for hospitals (Cornaggia, Li and Ye, 2024), age of the local tax base (Butler and Yi, 2022), and environmental regulations (Jha, Karolyi and Muller, 2025). We show that wildfire smoke is relevant not only to yields on local healthcare municipal bonds but also to those in nearby states, as traveling wildfire smoke plumes can impose significant cost externalities on these states' healthcare systems.

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

³Internet Appendix A.1 further provides a detailed review of the medical and epidemiological literature on wildfire smoke exposure, hospital utilization, and health outcomes.

II. Conceptual Framework for Wildfire Smoke Risk

The financial health economics theoretical framework in Koijen, Philipson and Uhlig (2016) provides a useful lens for framing and understanding how environmental risk may affect the cost of capital and investment in the healthcare industry. In their model, healthcare securities trade at a discount due to the “disaster risk” that the federal government will cut reimbursements for demand subsidy programs such as Medicare and Medicaid. As a result, entrepreneurs reduce investment spending on research and development in the healthcare industry. Applied to our setting, the predictions from their model imply the following: (1) healthcare municipal bonds may trade at a discount due to the disaster risk of increased wildfire smoke and the associated increase in healthcare service demand from unprofitable patient groups, and (2) local hospitals may reduce investment spending because of this disaster risk.

There are two important differences between the setting in Koijen, Philipson and Uhlig (2016) and ours. The first is that federal government reimbursement cuts affect the entire US healthcare industry, while wildfire smoke affects local US hospitals. This is useful for our purposes because we have greater geographic and time series variation in wildfire smoke and treated hospitals. Furthermore, because the US municipal bond market is highly geographically segmented due to tax considerations (Babina et al., 2021), local investors are more likely to price local municipal bonds and incorporate the risks associated with local wildfire smoke. The second is that the reimbursement cuts in Koijen, Philipson and Uhlig (2016) have unambiguous effects on hospital credit risk and profit margins. By contrast, wildfire smoke has unclear effects, as the associated increase in demand for healthcare services could increase or decrease profit margins, depending on the incremental patient mix. This is ultimately an empirical question, and where our study comes in.

In a related study, Cornaggia et al. (2022) show that opioid abuse is causally associated with worse municipal finance outcomes through the capital supply channel. Opioid abuse and wildfire smoke can both lead to public health crises in affected areas, although the economic outcomes and implications differ in important ways. In our setting, we conceptualize that wildfire smoke increases hospital credit risk, especially in areas with greater healthcare service demand from unprofitable patient groups. An important and distinct implication is that underinsurance in the US can exacerbate negative financial effects stemming from public health crises. A second implication is that wildfire mismanagement can impose negative public health and financial externalities on distant regions with vulnerable populations. By contrast, the negative financial outcomes stemming from other natural disasters or public health crises tend to remain localized.

In a second related study, Gao, Lee and Murphy (2022) show that the state-level expansion of Medicaid insurance under the ACA reduces municipal borrowing costs in the healthcare industry. Hence, along the intensive margin, we hypothesize that hospital finances are less robust to public health crises in high-underinsurance markets, and thus, municipal healthcare investors' perspective on wildfire smoke risk is sensitive to the availability of Medicaid insurance. An important implication of this hypothesis is that a federal or state rollback of Medicaid or Medicare funding can amplify adverse public health effects from wildfire smoke on hospital finances and feed back into the municipal credit market.

III. Data and Summary Statistics

A. *Municipal Bonds*

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

We also collect data on secondary municipal bond yields from the Municipal Securities Rulemaking Board (MSRB) Electronic Municipal Market Access (EMMA) database from 2010 to 2019. We aggregate the data to the bond-year-month level by calculating the trade size-weighted average secondary yield across customer buy transactions. We exclude bonds with fewer than ten transactions and limit the sample to seasoned bonds outstanding for at least one year. Similar to the offering yield spread, we calculate the secondary yield spread

⁴Following Longstaff, Mithal and Neis (2005), the coupon-equivalent risk-free rate is calculated as follows. First, for each municipal bond, we calculate the present value of its future payments using the risk-free yield curve from Gürkaynak, Sack and Wright (2007) to obtain its risk-free price. Second, we calculate the yield-to-maturity on the municipal bond using its payment schedule and the risk-free price to obtain its coupon-equivalent risk-free rate.

as the secondary yield minus the coupon-equivalent risk-free rate.

We supplement our municipal bond data with information from Bloomberg on the US county associated with each issue, allowing us to merge the municipal bond data with county-level wildfire smoke pollution data. We also supplement our municipal data with county demographic information from the US Census Bureau’s ACS database. Following other municipal bond studies, we exclude outlier municipal bond records where (1) the maturity is over 100 years, (2) the offering yield exceeds 50 percentage points, (3) the coupon rate is variable or zero, (4) the issue is not exempt from federal taxes, and (5) the bond was issued outside of the continental US, where wildfire smoke pollution information is not available.

Table 1 reports summary statistics for our samples of healthcare issues (Panel A) and non-healthcare issues (Panel B). The healthcare issues comprise 5.3% of the sample by total issue size. These issues have a mean offering yield spread of 120.1 bps, issue size of \$63 million, maturity of 11.8 years, and rating number of 15.9 (approximately A2 on Moody’s credit rating scale). Non-healthcare issues have lower average offering yield spreads, higher credit ratings, smaller issue sizes, and shorter maturities. These issues are also more likely to be general obligation or insured and less likely to be callable or issued in the negotiated market. In our subsequent tests, we control for these differences in bond issue characteristics.

B. Wildfire Smoke Pollution

We obtain wildfire smoke pollution data at the daily census tract level from the Stanford Echo Lab. The data feature the predicted surface $PM_{2.5}$ concentrations from wildfire smoke plumes. Childs et al. (2022) construct these data using a machine learning algorithm that detects anomalous variations in pollution monitor readings of $PM_{2.5}$ on days when smoke from wildfires 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 $\text{PM}_{2.5}$ 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 $\text{PM}_{2.5}$ 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 particular, we calculate the population-weighted annual cumulative $\text{PM}_{2.5}$ exposure across census tracts within each county, with population shares weighted to the 2014 ACS 5-year population estimates. Our measures of $\text{PM}_{2.5}$ exclude $\text{PM}_{2.5}$ originating from non-wildfire sources. We refer to the population-weighted annual cumulative wildfire smoke $\text{PM}_{2.5}$ measure from the Stanford Echo Lab as simply *Smoke* for brevity and exposition.

We observe significant time series and cross-state variation in wildfire smoke pollution. Table 2 and Figure 1 provide summary statistics for our *Smoke* metric by year. These statistics indicate that wildfire smoke pollution has been steadily trending upward over time, with large spikes in some years that double the amount of wildfire smoke pollution compared to previous years. Figures 2, Panels (a) to (f) illustrate the geographic variation in *Smoke* exposure by year. To get a sense of relative changes over time, *Smoke* is standardized here 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 early in the decade but has shifted to the Western US, with exposure intensity spilling over into states in other regions.

C. Hospital and Insurance Data

We collect supplementary information on hospital finances, insurance coverage, and ER usage from several sources. First, we collect hospital-year data spanning 2012–2019 from the HCRIS database. This database contains detailed hospital financial information such as total revenue, total cost, and fixed asset value.⁵ Second, we collect information on county-level health insurance coverage from the American Community Survey (ACS) Small Area Health Insurance Estimates (SAHIE) database, which includes statistics on insured and uninsured patients in each county-year. Third, we collect US Census Bureau data on local health insurance statistics, including information on Medicare and Medicaid patients. Lastly, we collect emergency department visit data from the Nationwide Emergency Department Sample (NEDS), a Healthcare Cost and Utilization Project (HCUP) database maintained by the Agency for Healthcare Research and Quality (AHRQ). NEDS is a nationally representative all-payer emergency department database in the United States and contains categorized information on expected payer status, including Medicare, Medicaid, Private Insurance, Self Pay, and No Charge.

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

IV. Wildfire Smoke and Healthcare Borrowing Costs

A. Baseline Tests

We test the effect of smoke pollution on the borrowing costs of healthcare municipal bond issues relative to non-healthcare issues in that county. Our empirical model employs a continuous treatment design in which all observations are treated but at varying “dosage” levels with different expected intensity effects. 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 standardized annual population-weighted cumulative PM_{2.5} exposure across census tracts within each county j . The PM_{2.5} exposure in county j comes from one or more fires that occurred during that year (including out-of-state fires), and not from non-wildfire sources such as local industrial activity or traffic congestion.

Formally, we test the following ordinary least squares (OLS) regression model:

$$\begin{aligned} y_{ijt} = & \beta^C \cdot Smoke_{jt} + \beta^H \cdot Smoke_{jt} \times Health_i + \gamma \cdot X_{ijt} + \delta \cdot Z_{it} \\ & + \rho_j + \psi_{st} + \phi_{it} + \varepsilon_{ijt}, \end{aligned} \quad (1)$$

where $Health$ is an indicator variable that equals one if the municipal bond issue was used to finance a healthcare project. The β^C coefficient measures the effect of $Smoke$ on non-healthcare yield spreads, and the β^H coefficient measures the incremental effect of $Smoke$ on healthcare yield spreads, respectively. The issue-level control variable vector X consists of the standalone $Health$ indicator variable, the natural logs of issue size and the size-weighted number of years until maturity, and indicator variables for whether the bond is a general obligation and whether it is issued in the negotiated market. The county-level

control variable vector Z consists of the natural logs of population, per capita income, and median gross rent, the Hispanic and Black population shares, the housing vacancy rate, and the renter-to-owner occupancy ratio. ρ_j is a vector of county fixed effects and ψ_{st} is a vector of State $\times$ Year-Month fixed effects. ϕ_{it} is a vector of Rating $\times$ Year-Month, Insured $\times$ Year-Month, and Callable $\times$ Year-Month fixed effects, and is meant to control for bond factors such as insurance value that may have a time-varying effect on yield spread (Cornaggia, Hund and Nguyen, 2024). Rating is the average bond rating in that county, and is meant to capture the average risk exposure of bonds issued in the county, independent of *Smoke* shocks in any particular year. Standard errors are double-clustered at the county and year-month levels.

There are three key identifying assumptions that are implicit in this model. First, the level of smoke exposure was not anticipated at the time of bond issuance. Second, healthcare bond yields would have experienced a similar trend as non-healthcare bond yields in the absence of *Smoke*, which ultimately affects demand for the underlying healthcare service providers. In other words, the response intensity should be much greater among healthcare bonds than non-healthcare bonds. Third, healthcare bonds with a higher *Smoke* dosage would have experienced a similar yield effect to healthcare bonds with a lower smoke dosage if the former had instead been exposed to the same low dosage, and vice versa (see Callaway, Goodman-Bacon and Sant’Anna, 2024). Our identifying assumptions need only hold conditional on the controls and fixed effects in equation (1).

Table 3, column (1) first reports the OLS estimates from equation (1) without the fixed effect vector ϕ_{it} . We find that a one standard deviation increase in *Smoke* is associated with a 7.0 bps increase in the offering yield spread for healthcare issues relative to non-healthcare issues, and no change in the offering yield spread for non-healthcare issues. In column (2),

we include ϕ_{it} , and find a similar $Health \times Smoke$ point estimate of 6.7 bps. In column (3), we include County $\times$ Year-Month fixed effects to force a comparison of healthcare versus non-healthcare bonds within the same county-year-month. We lose about 40% of our sample in this case, but find a stronger point estimate of 13.0 bps. In column (4), we repeat the same test in column (3), except that we use only industrial development bonds in our control group of non-healthcare bonds; wildfire smoke is especially unlikely to be relevant or salient in the industrial development market. In this case, we find an even larger $Health \times Smoke$ point estimate of 17.2 bps. Overall, these findings indicate that wildfire smoke increases credit risk for treated issuers in the healthcare industry. Furthermore, these findings are consistent with our key identifying assumptions, as the time-varying fixed effects allow us to control for location-specific time trends that may be influencing bond yields differently.⁶

Lastly, in column (5), we re-test the baseline model in equation (1), except that we use the secondary yield spread as the outcome variable and include bond fixed effects. This specification forces a within-bond comparison of yield changes following a dosage of *Smoke*, and thus mitigates concerns about unobservable characteristics that may influence the results. Because some bonds trade significantly more than others and thus are overrepresented in the sample, we estimate the model using weighted least squares (WLS) with analytic weights equal to the inverse of the number of customer buy transactions for each bond. The results in column (5) indicate that a one standard deviation increase in *Smoke* is associated with a

⁶The larger point estimates in columns (3) and (4) may reflect a combination of effect heterogeneity and changes in sample composition. For instance, because County $\times$ Year-Month fixed effects require more demanding comparisons for identification, they may place greater weight on highly populated counties with more frequent bond issuance. Furthermore, as we show in subsequent tests, smoke effects may vary depending on the underlying population, the operational capacity of the local healthcare system, and the risk of non-payment among admitted patients. There may also be differences in unobservable issue-level characteristics between healthcare and non-healthcare bonds that correlate spatially. Thus, unless otherwise stated, we continue to employ the baseline model in equation (1) as our main specification throughout our analysis of yield outcomes.

4.8 bps increase in the relative healthcare secondary yield spreads, which is slightly weaker than but comparable to the healthcare offering yield effect of 6.7 bps.

As a visual robustness test, we follow Borgschulte, Molitor and Zou (2022) and augment our model in column (5) with the one-year and two-year leads and lags of *Smoke* and their interactions with *Health*. The lagged terms allow us to examine whether past *Smoke* exposure has a persistent effect on healthcare yield spreads. Meanwhile, the lead terms serve as placebo checks since future *Smoke* exposure should not be associated with current yield spreads if healthcare and non-healthcare bonds do not exhibit differential preexisting trends that correlate with subsequent *Smoke* shocks. We report the coefficients of the leads and lags of $Health \times Smoke$ in Figure 3. The figure indicates that the contemporary *Smoke* effect on secondary healthcare bond yields is statistically significant at the 5% level (5.6 bps), whereas the point estimates for the lags and leads of $Health \times Smoke$ are not statistically significant. Overall, these results suggest that the healthcare municipal bond market efficiently incorporates information from *Smoke* into yields. Furthermore, the figure indicates that secondary healthcare yields do not diverge significantly in response to lead *Smoke* shocks, supporting the parallel trends assumption.

The effect of *Smoke* on healthcare borrowing costs is highly economically significant. For healthcare service providers, our baseline estimated effect of 6.7 bps represents 7.5% of one standard deviation in the healthcare offering yield spread (88.9 bps), 7.2% of the credit spread between Aaa and Baa1 bonds (92.8 bps), and \$170 million in additional present value interest costs on the \$25.4 billion worth of healthcare municipal bonds issued in above-mean *Smoke* counties. If average annual exposure to wildfire smoke pollution were to increase again by $72 \mu g/m^3$ over the next decade based on current smoke trends (66.1% of one standard deviation in our cumulative $PM_{2.5}$ exposure measure), then our point estimates suggest that

repeat issues of healthcare municipal bonds from our main sample period would amount to another \$509 million in out-of-sample present value interest costs.⁷ Lastly, Goldsmith-Pinkham et al. (2023) use the Merton (1974) structural model to map yield changes onto the plane of possible changes in underlying asset value and volatility. The estimates in Figure 6 of Goldsmith-Pinkham et al. (2023) suggest that the 6.7 bps yield effect documented in this study corresponds to a 2.5% to 7.5% decrease in hospital asset value, a 2.0% to 4.0% increase in hospital asset volatility, or a convex combination of the two changes.

Robustness tests in Internet Appendix A.2 indicate that our results are not affected by correlated economic shocks from direct physical wildfire damages or alternative definitions of the yield spread. In particular, columns (1) to (4) of Table A.1 show that the $Health \times Smoke$ point estimate from our baseline specification remains 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, the exclusion of California, where a large number of wildfires occur during our sample period, or the combined exclusion of county-years with wildfire events and California. Hence, our central findings are unaffected by correlated economic shocks that could have been driven by direct physical damages from the wildfires themselves. In Table A.2, columns (1) to (3), we show that our baseline results are unaffected if we use the tax-adjusted yield spread (Garrett et al., 2023) or call-adjusted yield spread (Novy-Marx and Rauh, 2012) as the dependent variable, or if we focus on issues in the post-summer months of September to December when the wildfire season has largely concluded. Lastly, in columns (4) and (5) of Table A.2, we show that our baseline results for the offering market

⁷The present value interest costs are calculated using the duration approximation formula: (1) \$170 million $\approx 0.00067 \times 10 \times \$25.4$ billion, where 10 years is the average duration for a healthcare issue and the average *Smoke* value is approximately one for counties with above-mean *Smoke*, and (2) \$509 million $\approx 0.661 \times 0.00067 \times 10 \times \$115$ billion, where \$115 billion is the total size of healthcare issues during our sample period.

and the secondary market are robust to using a standardized 12-month moving average of wildfire smoke pollution.

B. Underinsurance and Hospital Credit Risk

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

Methodologically, we collect county-year insurance information from the US Census Bureau’s ACS database and define the underinsured population as the sum of uninsured, Medicaid-insured, or Medicare-insured residents. For our purposes, the latter two categories are included in the underinsured definition because average profit margins associated with all three categories are negative (Wilson and Cutler, 2014). Additionally, we infer county-level hospital counts from HCRIS cost reports to proxy for operational patient capacity. We define *Underins/Hosp* (*UndH*) as the standardized natural log of the average number of underinsured residents per hospital in the county. We retest the regression model in equation (1) for the subsamples of above-median *UndH* (“high underinsurance”) counties and below-median *UndH* (“low underinsurance”) counties.

The results are reported in columns (1) and (2) of Table 4. These results indicate that a one standard deviation increase in *Smoke* is associated with a statistically significant 9.3 bps increase in healthcare borrowing costs in high underinsurance counties, and a statistically insignificant 4.9 bps increase in healthcare borrowing costs in low underinsurance counties,

for a difference of 4.4 bps. In column (3), we re-test the same regression model, except that we use our full sample of counties, and also interact $Health \times Smoke$ with $UndH$. (The associated single-interaction and double-interaction terms are also included in this regression.) The point estimate on the triple interaction term is a statistically significant 5.2 bps, reflecting the evidence from the subsample regressions. Lastly, in column (4), we retest the model in column (3), except that we use only industrial bonds as our control group. In this case, we find a stronger point estimate on the triple interaction term of 9.2 bps. Overall, the evidence from these regressions is consistent with the expectation that *Smoke* increases healthcare service demand among unprofitable patient groups, and that the market prices the associated bonds accordingly.

C. Identification through Medicaid-Expansion

Although we cannot randomly assign the population of underinsured residents, the staggered state-level expansion of Medicaid eligibility sharpens identification of the underinsurance channel. Along the intensive margin, an increase in overall profitability from underinsured patients may offset the stronger *Smoke*-yield effects observed in high-underinsurance counties. We test this prediction using the staggered expansion of Medicaid from 2012 to 2019 as part of the ACA. Testing this prediction sharpens identification of the underinsurance channel since state-level decisions to expand Medicaid were largely political and uncorrelated with local economic conditions (Gao, Lee and Murphy, 2022).

To provide some background, the original ACA was signed into law in 2010 under the Obama administration. The law initially required states to expand Medicaid eligibility to all households with incomes below 138% of the federal poverty line (FPL), effectively reducing the share of uninsured residents in the underinsured category. Before the passage of the

ACA, many states capped eligibility below the FPL and limited coverage to families with children. (For reference, in 2009, the FPL was \$10,830 for the first person in a household, and an additional \$3,740 for each additional person in that household.) Additionally, the ACA established a federal government commitment to subsidize 90% of the Medicaid expansion costs across all states in the long term, increasing reimbursement expectations for treating underinsured patients (Gao, Lee and Murphy, 2022).

In June 2012, the Supreme Court ruled that states could not be required to expand Medicaid eligibility under the ACA, even as the court upheld the law’s constitutionality. Since that ruling, 40 states have expanded Medicaid at different times (Gao, Lee and Murphy, 2022). Within those 40 states, a significant number of eligible residents became Medicaid-insured after previously being uninsured. As a result, average hospital profit margins from underinsured patients improved, especially in high-underinsurance counties where Medicaid expansion shifted more demand out of the uninsured category (where profit margins are highly negative) and into the Medicaid-insured category (where profit margins are higher) (Wilson and Cutler, 2014).⁸ We conjecture that investors in the healthcare municipal bond market recognize that hospitals are more financially resilient to *Smoke*-induced shocks if a greater percentage of patients are Medicaid-insured as opposed to uninsured.

Methodologically, we retest the triple-interaction regression model from column (3) of Table 4, except that we use the following subsamples: $MedExp = 0$ (the state has not expanded Medicaid as of that year-month) and $MedExp = 1$ (the state has expanded Medicaid as of that year-month). The results are reported in columns (1) and (2) of Table 5. For the $MedExp = 0$ subsample in column (1), the statistically significant point estimate on

⁸We should also note that the size of the underinsured population does not mechanically change around the expansion of Medicaid because the uninsured and Medicaid-insured groups remain jointly classified as underinsured in our *Underins/Hosp* measure. Further, there was no significant migration of patients from the private-insured group to the Medicaid-insured group.

$Health \times Smoke \times UndH$ indicates that a one standard deviation increase in $Smoke$ is associated with a 6.3 bps increase in healthcare borrowing costs if $UndH$ is also one standard deviation higher than its mean. By contrast, for the $MedExp = 1$ subsample in column (2), the statistically insignificant point estimate on $Health \times Smoke \times UndH$ indicates that underinsurance does not exacerbate the $Smoke$ effect on healthcare yields.

In column (3) of Table 5, we retest the same regression model, except that we use our full sample and include the interaction of $Health \times Smoke \times UndH$ with $MedExp$. (We also include the double-interactions and triple-interactions associated with these four variables.) Reflecting the evidence in column (1), we find that the $Smoke$ -induced healthcare yield effect is significantly higher (7.2 bps) if $UndH$ is one standard deviation above its mean. Importantly, we also find a negative and statistically significant point estimate on $Health \times MedExp \times Smoke \times UndH$ (-8.0 bps), thereby indicating that the incremental 7.2 bps $Smoke$ effect in high underinsurance counties is virtually nullified by the expansion of Medicaid in that state. Lastly, in column (4), we obtain similar conclusions if we instead use industrial development bonds as the control group. These findings suggest that an increase in the average profitability of underinsured patients through state-level Medicaid expansion offsets the incremental effect of $Smoke$ on healthcare yields in high-underinsurance counties. An implication of this finding is that limiting access to Medicaid or reducing Medicaid reimbursement rates would amplify the adverse impact of wildfire smoke exposure on hospital borrowing costs.

D. Cross-Border Externalities

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.

In this section, we analyze how drifting wildfire smoke plumes affect borrowing costs for healthcare providers in nearby states. These tests allow us to further separate wildfire smoke pollution from its wildfire source and quantify costs to nearby states through the smoke channel.

Methodologically, we decompose our *Smoke* variable into two components using 2010–2020 wildfire data 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:

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

where F_{sy} is a vector of observed in-state wildfire variables, including the number of wildfires, the number of structures damaged, and the natural log of burned acres in state s and year y .⁹ To account for geographic and meteorological differences in the relationship between in-state wildfire activity and local smoke exposure, we interact F_{sy} with state fixed effects (δ_s). The predicted component from this equation captures the portion of *Smoke* attributed to in-state wildfire activity (*HomeSmoke*), and the residual component captures the portion of *Smoke* not explained by observed in-state wildfire activity (*AwaySmoke*). For ease of interpretation, we standardize both components of wildfire smoke.

We retest the baseline regression model in equation (1), except that we replace *Smoke* with *HomeSmoke* and *AwaySmoke*. The results are reported in column (1) of Table 6. We find that *HomeSmoke* and *AwaySmoke* significantly increase healthcare borrowing costs. A one standard deviation increase in *HomeSmoke* is associated with a 10.6 bps increase

⁹To 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).

in healthcare borrowing costs, and a one standard deviation increase in *AwaySmoke* is associated with a 7.3 bps increase in healthcare borrowing costs. We find that the $Health \times HomeSmoke$ coefficient is also not statistically different from the $Health \times AwaySmoke$ coefficient. In column (2), we retest the same regression model in column (1), except that we use only industrial development bonds as our baseline instead of all non-healthcare bonds, and also find that the $Health \times HomeSmoke$ and $Health \times AwaySmoke$ point estimates are similar in magnitude.

In column (3), we examine cross-sectional heterogeneity in the *Smoke*-yield relationship by interacting $Health \times HomeSmoke$ and $Health \times AwaySmoke$ with *UndH*, the underinsurance rate. We find that *HomeSmoke* and *AwaySmoke* increase healthcare borrowing costs by an additional 7.9 bps and 4.6 bps, respectively, if *UndH* is one standard deviation above its mean. Lastly, in column (4), we draw similar conclusions when comparing healthcare issues to industrial development issues in the cross-section of *UndH*. Our findings are consistent with the interpretation that in-state and out-of-state wildfire smoke significantly increase healthcare borrowing costs, especially in areas with a high rate of underinsurance.

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. That same year, out-of-state smoke in neighboring Nevada was about 2.5 standard deviations above its mean. Our point estimates in Table 6 indicate that healthcare borrowing costs would have increased by $7.3 \times 2.5 = 18.3$ bps due to the out-of-state smoke. For a hospital issue with an average size of \$90 million and a duration of ten years, the out-of-state smoke effect would increase total present value interest costs by about \$1.65 million.

Should we classify the average *AwaySmoke* effect as a cross-state negative externality

or spillover? If a state spends less on wildfire prevention and does not compensate health-care providers in nearby states for the financial costs associated with drifting smoke plumes, then the “externality” classification is more appropriate. Internet Appendix A.3 and Table A.3 provide a case study and descriptive evidence on wildfire prevention and suppression expenditures in California. Relative to other states in the Western US, California has higher fire-suppression expenditures per acre and lower federal hazardous fuel treatment expenditures per acre. While a causal analysis of wildfire prevention expenditures and *AwaySmoke* is outside the scope of this study, these descriptive patterns are consistent with the notion that differences in wildfire mitigation and suppression activity may contribute to cross-state smoke exposure. However, because the expenditure data partially capture federal hazardous fuel treatment spending on federal lands, rather than total state-chosen wildfire prevention spending, we interpret this evidence as suggestive and do not use it to identify the causal effect of prevention spending on *AwaySmoke* or healthcare borrowing costs.

V. Hospital Outcomes

In this section, we test if *Smoke* leads to adverse hospital-level outcomes that are internally consistent with the increase in hospital credit risk. First, we test if *Smoke* increases unprofitable ER visits to hospitals using information on ER visits from different insurance groups. Second, using a panel of hospital-year data from HCRIS, we examine whether *Smoke* is associated with lower subsequent hospital investment activity, and whether the investment response varies with the local underinsurance rate. Third, using the same panel of hospital-year data, we test the association between *Smoke* and hospital profit margins, and whether the association also varies with the local underinsurance rate.

A. *Wildfire Smoke and ER Visits*

The first step of our analysis of real outcomes is to test whether *Smoke* is positively associated with hospital ER admissions, thereby providing internal validity for our proposed mechanism and external validity for related studies on the adverse health effects of air pollution (e.g., Aguilera et al., 2021; Heft-Neal et al., 2023). We use emergency department discharge data from the AHRQ NEDS/HCUP database, which covers 35 states from 2010 to 2019. This database comprises state-quarter records on adult and pediatric ER visits by insurance group (e.g., privately-insured, Medicaid-insured, uninsured). We recalibrate our *Smoke* measure to capture the standardized total population-weighted PM_{2.5} exposure at the state-quarter level, and regress the natural log of ER admissions on *Smoke*. The regression model includes state and year-quarter fixed effects, and the standard errors are clustered by state.

The results are reported in Panel A of Table 7. In column (1), we find that a one standard deviation increase in quarterly *Smoke* is associated with a statistically significant 0.9% increase in quarterly ER visits, or approximately 2.7 ER visits per 10,000 residents per quarter. In California, which has a population of approximately 39.4 million people, a one standard deviation increase in *Smoke* would be associated with about 10,638 additional quarterly ER visits. In columns (2) and (3), we instead use underinsured and privately-insured ER visits as the outcome variables, and find that a one standard deviation increase in *Smoke* is associated with a 0.8% increase in ER visits from either group. Lastly, in column (4), we show that *Smoke* does not significantly affect the ratio of underinsured to privately-insured ER visits. Because underinsured residents significantly outnumber privately insured residents, the average hospital will receive more demand from the former group, even if the

percentage effects are similar.¹⁰

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

B. *Wildfire Smoke and Investment*

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

¹⁰In Panel B of Table 7, we retest the same regressions from Panel A, except that we use available data on pediatric asthma ER visits from AHRQ as the outcome variable. Consistent with evidence in Noah et al. (2023) and Wilgus and Merchant (2024), we find that *Smoke* is associated with a significant increase in pediatric asthma ER visits as well. Consistent with Panel A, we also find that the percentage of pediatric asthma ER visits similarly increases across insurance categories.

hospitals.

Adapting the methodology from Adelino, Lewellen and Sundaram (2015), we use hospital financial variables from the HCRIS database to test the effect of *Smoke* on nonprofit hospital investment spending. The main dependent variables used for these tests are the future one-year and two-year growth rates in net fixed assets for each hospital h in county j and year t , $g(NFA)_{h,j,t+1}$ and $g(NFA)_{h,j,t+2}$, and the main independent variable is *Smoke*. In a standard OLS regression that uses these variables as inputs, the point estimate on *Smoke* captures the effect of wildfire smoke pollution on future investment spending.

Formally, we test the following OLS regression model:

$$g(NFA)_{h,j,t+k} = \beta_1 \cdot Smoke_{j,t} + \delta \cdot X_{h,j,t} + \phi_{i,j,y} + \varepsilon_{h,j,t}, \quad (3)$$

where $k \in \{1, 2\}$, $g(NFA)_{h,j,t+k}$ is the future k -year growth rate in net fixed assets for hospital h in county j and year t , and $\phi_{i,j,y}$ is a vector of State $\times$ Year and hospital fixed effects. The control variable vector $X_{h,j,t}$ from Adelino, Lewellen and Sundaram (2015) includes the following: $g(SRev)$, the percentage change in hospital net service revenue from $t - 1$ to t ; $OpInc$, the ratio of operating income in year t to net fixed assets in year $t - 1$; $\log(TRev)$, the natural log of total revenue in year t ; and $FinInv$, the ratio of financial investment value to net fixed assets for the hospital in year $t - 1$. The summary statistics in Table 8 indicate that the variable distributions are similar to those reported in Adelino, Lewellen and Sundaram (2015).

The regression results are reported in Table 9. Column (1) indicates that a one standard deviation increase in *Smoke* is associated with a 4.8 percentage point decrease in two-year net fixed asset growth that is statistically significant at the 5% level, and column (3) shows a

smaller and statistically insignificant 1.4 percentage point decrease in one-year net fixed asset growth. The stronger effect at the two-year horizon reflects findings in Adelino, Lewellen and Sundaram (2015) that hospital investments are highly capital-intensive and require longer adjustment times. In columns (2) and (4), we expand equation (3) by interacting *Smoke* with *UndH* to examine heterogeneous *Smoke* effects in the cross-section of the underinsurance rate. The results in these columns indicate that *Smoke* continues to have a strong effect on investment at the two-year horizon for the average hospital (-4.7 percentage points), while *Smoke*×*UndH* has no incremental effect on hospital investment. Our baseline results suggest that municipal bond investors anticipate that profitability in *Smoke*-affected hospitals will be lower in the long run and price the associated bonds accordingly. The results in Table 9 indicate that the average *Smoke*-affected hospital responds by reducing investment activity.

C. Wildfire Smoke and Profit Margins

Lastly, we examine whether the increase in healthcare service demand associated with *Smoke* is reflected in overall hospital financial performance. We retest the same regression model from equation (3), except that we use hospital profit margin (*Margin*) as the outcome variable. *Margin* is calculated as the ratio of total hospital revenue minus total hospital expenses to total hospital expenses based on revenue and expense data from HCRIS. We standardize this measure for ease of interpretation.

The results in column (1) of Table 10 indicate that *Smoke* has no statistically significant effect on *Margin*, and column (2) indicates that the *Smoke* effect remains insignificant if we include the county-level controls from our baseline regression. However, in column (3), we retest the model in column (1), except that we interact *Smoke* with *Underins/Hosp*; in this case, we find that *Smoke* reduces *Margin* by 2.4% if *Underins/Hosp* is one standard

deviation above its mean. This result is consistent with our earlier intuition that *Smoke* increases unprofitable demand from underinsured patients. Lastly, in column (4), we continue to find a similar *Margin* result in the cross-section of *Underins/Hosp* if we include the county-level controls from our baseline regression model.

Our baseline results indicate that *Smoke*-treated hospitals in low-underinsurance counties experience a modest increase in borrowing costs and a reduction in investment activity. This response is consistent with the literature showing that reduced access to capital markets is associated with reduced investment (Adelino, Cunha and Ferreira, 2017). However, the results in this section show that *Smoke* does not have a significant effect on profit margins in low-underinsurance counties. Because profit margin is a contemporaneous outcome and borrowing costs and investment reflect anticipated outcomes over longer periods, our interpretation is that investors and hospitals respond to anticipated long-run *Smoke* effects, and not just *Smoke* effects on profits in the short run. Hospitals in high-underinsurance counties, by contrast, experience a reduction in short-run profits, a larger increase in long-run borrowing costs, and a decrease in future investment.

VI. Conclusion

Large-scale wildfires have become increasingly common over the last several decades, and the physical damages to areas in the associated burn regions are unprecedented. Municipalities downwind of wildfires may not suffer any physical damages, but they do incur the health and economic costs associated with poor air quality, even when the origin of the fire is in another state or country. These costs are expected to rise in many regions as wildfire smoke days become more frequent (First Street, 2024), raising the stakes for the sectors most

exposed to these adverse climate events.

Wildfire smoke pollution poses a unique risk to the healthcare sector because it increases demand for healthcare services, regardless of the insurance status of the patient. In many regions, underinsured patients outnumber privately-insured patients, and hospitals cannot perfectly ration healthcare services to treat only the most profitable patients. Using a novel measure of smoke exposure that is plausibly exogenous to local economic conditions, we show that *Smoke* is associated with significantly higher borrowing costs for healthcare service providers. Consistent with our proposed mechanism, the effect is especially pronounced in high-underinsurance counties where shifts in local demand for healthcare services can be highly unprofitable, and a natural experiment involving the expansion of Medicaid insurance eligibility supports a causal interpretation of the underinsurance channel. Out-of-state *Smoke* similarly increases the cost of capital for healthcare service providers, indicating that local wildfires impose negative cost externalities on healthcare service providers in nearby states. Hospital-level tests further show that *Smoke* is associated with reduced profits and investment growth, suggesting that hospitals with reduced access to capital markets through the *Smoke* channel respond by decreasing future investment activity.

The costs associated with preventing and suppressing wildfires are steadily increasing. Intergovernmental cooperation may be important when smoke crosses jurisdictional boundaries, especially given our evidence that out-of-state smoke imposes negative cost externalities in the form of increased healthcare borrowing costs, lower profit margins, and reduced investment. While our analysis does not causally estimate the effect of wildfire prevention spending on out-of-state smoke exposure, our results suggest that policymakers should consider the downstream financial costs of out-of-state smoke when evaluating wildfire mitigation and coordination policies. A key question policymakers should be asking is who is best suited

to determine how much to spend on wildfire mitigation in light of these externalities. For within-state smoke, if adjacent local governments cannot negotiate how to split the associated costs, the state government may step in to determine an optimal solution. For smoke that travels across state or international 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.
- Adelino, Manuel, Igor Cunha, and Miguel A Ferreira.** 2017. “The economic effects of public financing: Evidence from municipal bond ratings recalibration.” *The Review of Financial Studies*, 30(9): 3223–3268.
- 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.
- Aguilera, Rosana, Thomas Corringham, Alexander Gershunov, and Tarik Benmarhnia.** 2021. “Wildfire smoke impacts respiratory health more than fine particles from other sources: observational evidence from Southern California.” *Nature Communications*, 12(1): 1493.
- 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*, 72: 1214–1235.

- 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 Tsz-Nga Wong.** 2025. “Leveraging the disagreement on climate change: Theory and evidence.” *Journal of Political Economy*, 133(10): 3132–3166.
- 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.
- Betermier, Sebastien, Sara B Holland, and Sean Wilkoff.** 2024. “How do retiree health benefit promises affect municipal financing?” Working paper. McGill University.
- 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>.
- 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.
- Callaway, B., A. Goodman-Bacon, and P. H. C. Sant’Anna.** 2024. “Difference-in-differences with a continuous treatment.” *AEA Papers and Proceedings*, 114: 601–605.
- Callaway, Brantly, Andrew Goodman-Bacon, and Pedro H. C. Sant’Anna.** 2026. “Difference-in-Differences with a Continuous Treatment.” *American Economic Review*. Forthcoming.

- 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 PM_{2.5} for the contiguous US.” *Environmental Science & Technology*, 56(19): 13607–13621.
- Cookson, J. A., E. Gallagher, and P. Mulder.** 2026a. “Coverage neglect in homeowners insurance.” Working paper. Pennsylvania State University.
- Cookson, J. A., E. Gallagher, and P. Mulder.** 2026b. “Money to burn: Crowdfunding wildfire recovery.” *Journal of Finance*, forthcoming.
- Cornaggia, Kimberly, John Hund, and Giang Nguyen.** 2024. “The price of safety: The evolution of municipal bond insurance value.” *Management Science*, 70(4): 2330–2354.
- 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.
- 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.
- 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.
- First Street.** 2024. “Atrocious Air.” Retrieved at: <https://firststreet.org/research-library/atrocious-air>.
- Gao, Pengjie, Chang Lee, and Dermot Murphy.** 2022. “Good for your fiscal health? The effect of the Affordable Care Act on healthcare borrowing costs.” *Journal of Financial Economics*, 145(2): 464–488.
- 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.
- 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.

- Gongloff, Mark.** 2025. “Where There’s Smoke, There’s \$244 Billion a Year in Damage.” *Bloomberg Opinion*. Accessed August 3, 2026.
- 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.
- Issler, P., R. Stanton, C. Vergara-Alert, and N. Wallace.** 2024. “Housing and mortgage markets with climate risk: Evidence from wildfires in California.” Working paper. University of California, Berkeley.
- Jeon, Woongchan, Lint Barrage, and Kieran James Walsh.** 2025. “Pricing climate risks: Evidence from wildfires and municipal bonds.” *Economic Working Paper Series*, 25.
- 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.** 2025. “Polluting public funds: The effect of environmental regulations on municipal bonds.” *Management Science*, 72: 5048–5067.
- 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.
- 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.

- 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>.
- Merton, R. C.** 1974. “On the pricing of corporate debt: The risk structure of interest rates.” *Journal of Finance*, 29: 449–470.
- 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.
- Safford, Hugh D, Alison K Paulson, Zachary L Steel, Derek JN Young, and Rebecca B Wayman.** 2022. “The 2020 California fire season: A year like no other, a return to the past or a harbinger of the future?” *Global Ecology and Biogeography*, 31(10): 2005–2025.
- Sautner, Zacharias, Laurence Van Lent, Grigory Vilkov, and Ruishen Zhang.** 2023. “Firm-level climate change exposure.” *The Journal of Finance*, 78(3): 1449–1498.
- 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.
- Timms, Mariah, and Alyssa Lukpat.** 2026. “Canadian Wildfires Create Hazardous Air in Midwest and Northeast.” Updated July 16, 2026, 3:56 PM ET.
- UNEP.** 2022. “Spreading like Wildfire – The Rising Threat of Extraordinary Landscape Fires.” Technical report. United Nations Environment Programme.

- U.S. Dept. of Health and Human Services.** 2024. “The Emergency Medical Treatment and Labor Act (EMTALA).” Last updated September 11, 2024.
- van Binsbergen, Jules, João F Cocco, Marco Grotteria, and S Lakshmi Naaraayanan.** 2026. “The impact of carcinogenic risk exposure on housing values: Estimates from chemical reclassifications.” *The Review of Financial Studies*, 39(8): 2517–2548.
- 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

- Agency for Healthcare Research and Quality (AHRQ)** (n.d.). “HCUP Fast Stats: State trends in emergency department visits by payer (quarterly counts by hospitalization type and payer).” *U.S. Department of Health & Human Services*. <https://datatools.ahrq.gov/hcup-fast-stats/#downloads> (accessed September 12, 2025).
- 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).
- Health Forum, LLC** (2024). 1999–2022 AHA Annual Survey. <https://www.ahadata.com/aha-annual-survey-database>
- Healthcare Cost Report Information System Database** (2021). “HCRIS Hospitals.” <https://www.nber.org/research/data/hcris-hosp> (accessed August 3, 2021).
- Municipal Securities Rule Making Board Electronic Municipal Market Access** (2026). <https://emma.msrb.org/> (accessed August 25, 2026).
- 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).

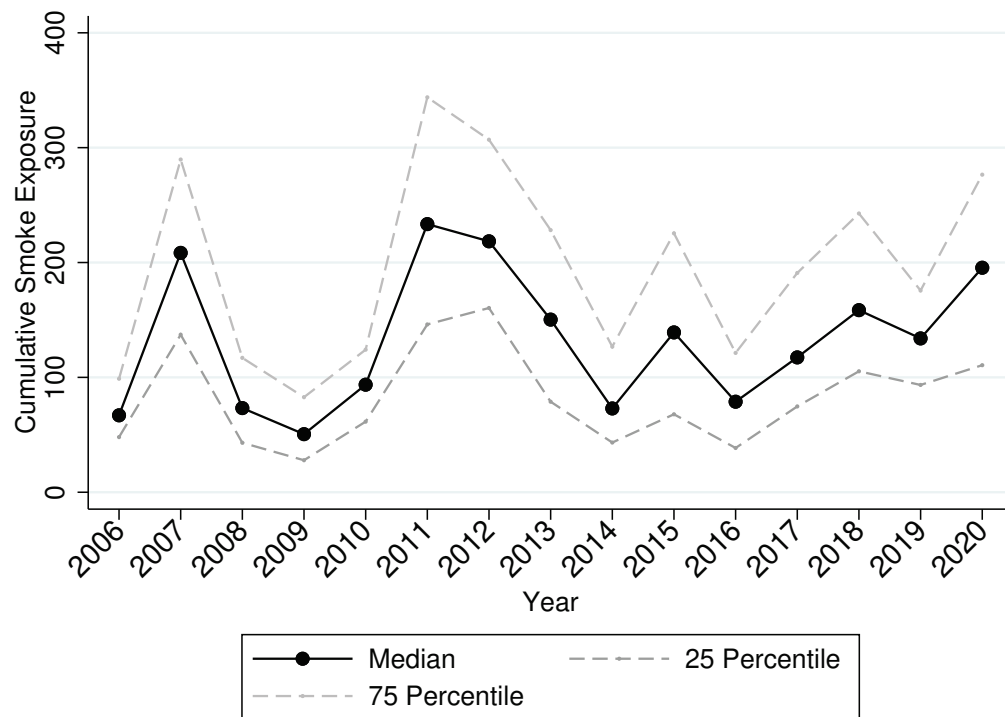


Figure 1. U.S. Wildfire Smoke by Year

This figure shows time-series statistics on county-level cumulative wildfire smoke exposure from 2006 to 2020. Annual cumulative wildfire smoke exposure for each county is population-weighted at the census tract level.

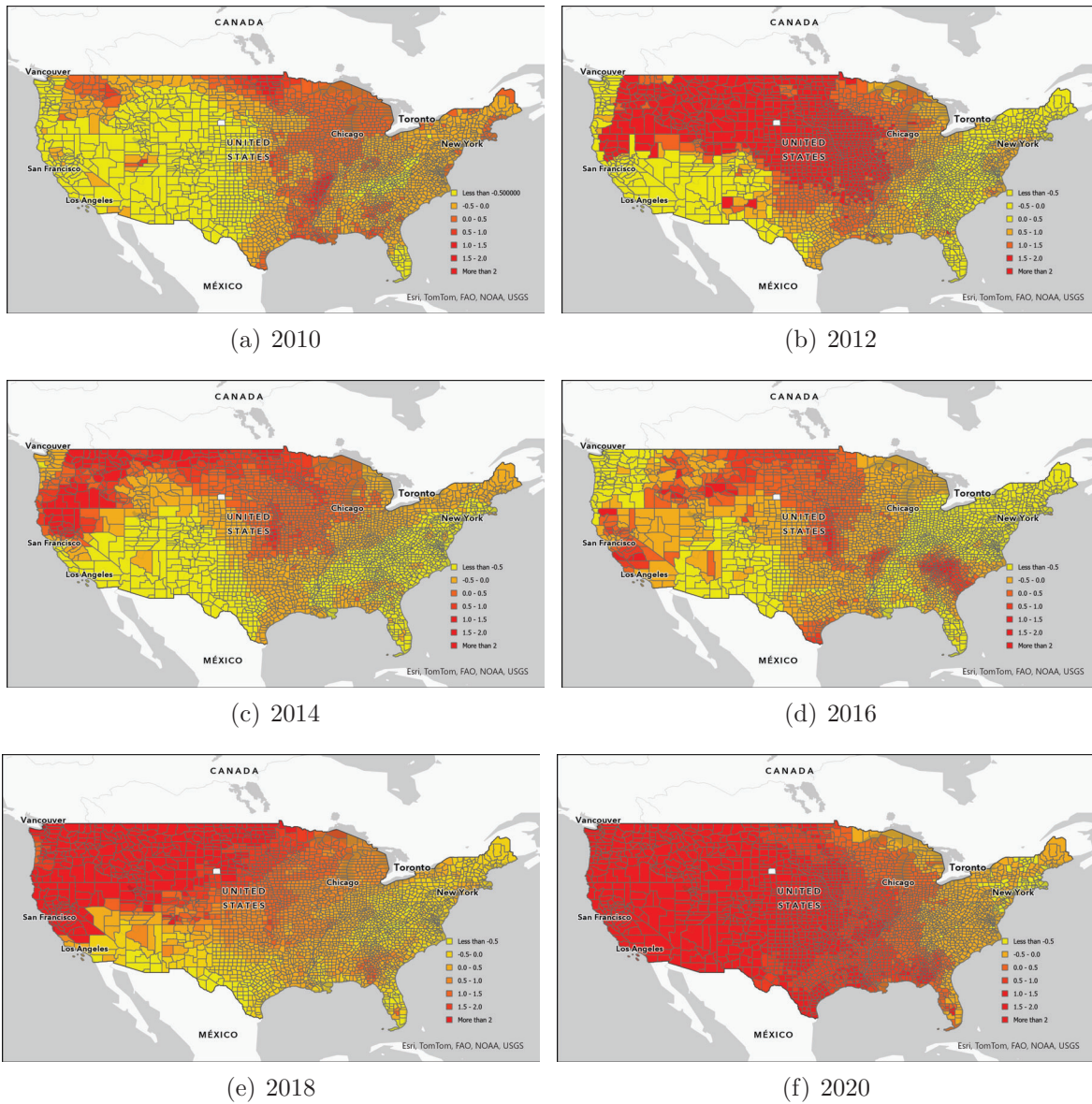


Figure 2. U.S. Wildfire Smoke Exposure

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.

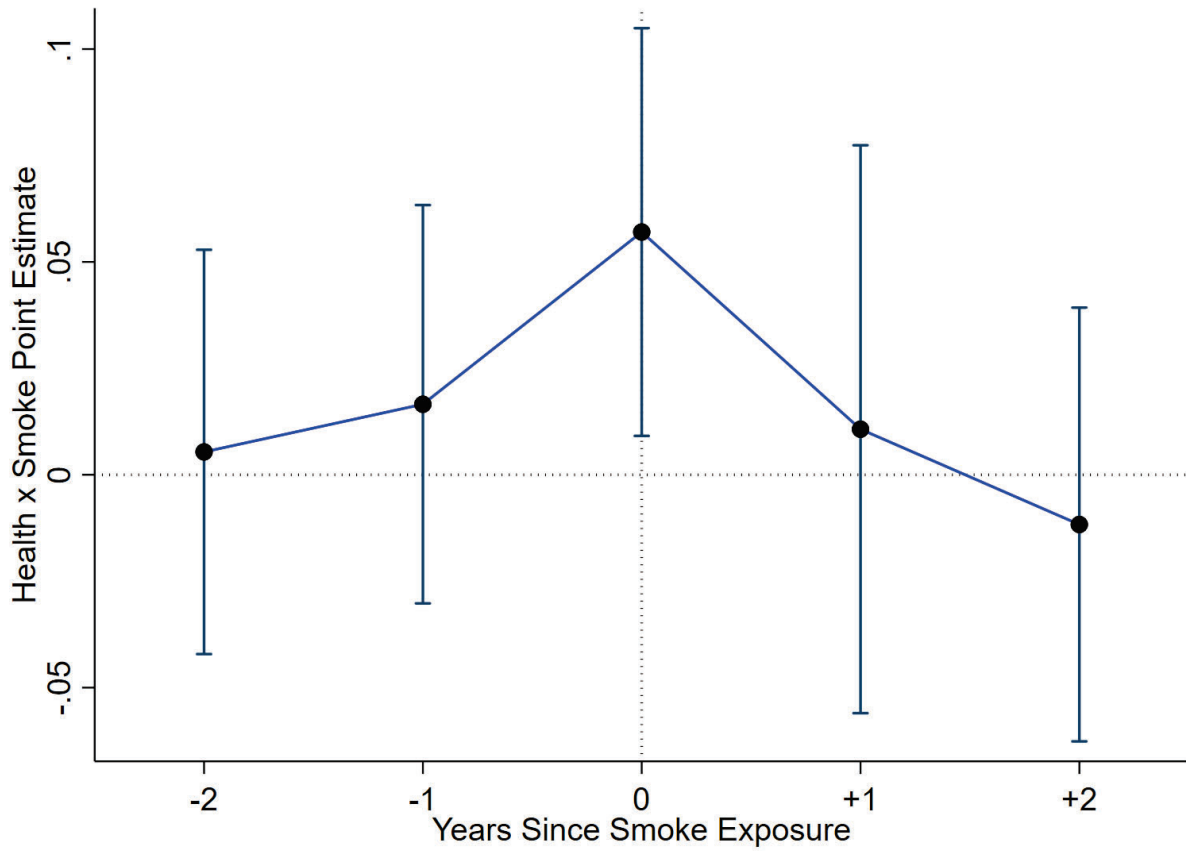


Figure 3. Lag/Lead Effects of Smoke on Healthcare Secondary Yield Spreads.

This figure reports the point estimates from a regression of secondary yield spread on $Health \times Smoke_y$, where $y \in \{-2, -1, 0, +1, +2\}$ is the year of smoke exposure relative to the secondary yield spread observation. Methodologically, we test our baseline secondary yield spread model in column (5) of Table 3, except that we also include the interactions of $Health$ with the one-year and two-year lags and leads of $Smoke$. The vertical bars are 95% confidence intervals for each $Health \times Smoke_y$ point estimate.

Table 1: Municipal Bond Summary Statistics by Sector

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

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

This table reports offering market summary statistics for healthcare municipal bond issues (Panel A) and non-healthcare municipal bond issues (Panel B) from 2010 to 2019.

Table 2: Wildfire Smoke Pollution Summary Statistics

	(1) Mean	(2) SD
2006	80.530	57.282
2007	223.566	138.171
2008	95.396	122.342
2009	60.500	41.738
2010	93.697	48.907
2011	251.727	140.227
2012	247.091	154.717
2013	158.325	106.096
2014	91.013	67.269
2015	173.958	158.386
2016	87.907	59.499
2017	184.599	240.326
2018	217.097	231.350
2019	140.465	64.905
2020	281.228	387.816
All Years	145.5	108.9
Decennial Change	71.5	139.4

Columns (1) and (2) report the mean and standard deviation of cumulative population-weighted smoke pollution ($\text{PM}_{2.5} \mu\text{g}/\text{m}^3$) exposure per year, respectively. Decennial Change is calculated as the average in 2016–2020 minus the average in 2006–2010.

Table 3: Wildfire Smoke Pollution and Healthcare Yield Spreads (%)

	(1) Yield Sp. (%)	(2) Yield Sp. (%)	(3) Yield Sp. (%)	(4) Yield Sp. (%)	(5) Yield Sp. (%)
<i>Smoke</i>	0.008 (0.007)	0.007 (0.006)			-0.014** (0.006)
<i>Health</i> $\times$ <i>Smoke</i>	0.070*** (0.026)	0.067*** (0.025)	0.130*** (0.046)	0.172** (0.070)	0.048** (0.019)
<i>Health</i>	0.676*** (0.035)	0.687*** (0.034)	0.721*** (0.054)	0.636*** (0.089)	
<i>lnSize</i>	-0.036*** (0.007)	-0.036*** (0.007)	-0.046*** (0.010)	-0.032*** (0.011)	
<i>Negotiated</i>	0.100*** (0.015)	0.102*** (0.014)	0.109*** (0.023)	0.118*** (0.035)	
<i>GenObligation</i>	-0.274*** (0.017)	-0.271*** (0.017)	-0.254*** (0.030)	-0.254*** (0.040)	
<i>lnMaturity</i>	0.170*** (0.018)	0.153*** (0.021)	0.150*** (0.029)	0.078*** (0.025)	-0.154*** (0.014)
County Controls	Yes	Yes	No	No	Yes
State-YM FE	Yes	Yes	No	No	Yes
Rating-YM FE	No	Yes	No	No	Yes
Insured-YM FE	No	Yes	Yes	Yes	Yes
Callable-YM FE	No	Yes	Yes	Yes	Yes
County FE	Yes	Yes	No	No	No
County-YM FE	No	No	Yes	Yes	No
Bond FE	No	No	No	No	Yes
Baseline	Non-HC	Non-HC	Non-HC	Ind. Dev.	Non-HC
Sample	OffMkt	OffMkt	OffMkt	OffMkt	SecMkt
Adj. R^2	0.503	0.514	0.518	0.581	0.806
N	68,030	67,780	40,529	12,876	7,763,120

This table reports regression estimates of the effects of wildfire smoke pollution on municipal borrowing costs. The dependent variable is offering yield spread or secondary yield spread (%), and the main independent variables are *Smoke* and *Health* $\times$ *Smoke*. *Smoke* is the standardized population-weighted cumulative amount of smoke PM_{2.5} exposure during the county-year. Columns (1), (2), (3), and (5) use all non-healthcare bonds (Non-HC) as the baseline group, and column (4) uses only industrial development bonds as the baseline group. Columns (1) to (4) use yield spread data from the offering market, and column (5) uses yield spread data from the secondary market. In column (5), secondary yield observations are inverse-weighted based on trade frequency, and observations within one year of issuance are excluded. The control variables are specified in the main text. Robust standard errors clustered by county and year-month are reported in parentheses. The stars *, **, ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4: Wildfire Smoke Pollution and Underinsurance

	(1)	(2)	(3)	(4)
	Yield Sp. (%)	Yield Sp. (%)	Yield Sp. (%)	Yield Sp. (%)
<i>Smoke</i>	0.009 (0.008)	-0.008 (0.010)	0.007 (0.006)	0.015 (0.011)
<i>Health</i> $\times$ <i>Smoke</i>	0.093** (0.043)	0.049 (0.036)	0.095*** (0.027)	0.142*** (0.037)
<i>Smoke</i> $\times$ <i>UndH</i>			0.004 (0.003)	-0.008 (0.006)
<i>Health</i> $\times$ <i>Smoke</i> $\times$ <i>UndH</i>			0.052*** (0.019)	0.092*** (0.025)
Controls	Yes	Yes	Yes	Yes
State-YM FE	Yes	Yes	Yes	Yes
Rating-YM FE	Yes	Yes	Yes	Yes
Insured-YM FE	Yes	Yes	Yes	Yes
Callable-YM FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Underins. Type	High	Low	All	All
Baseline	Non-HC	Non-HC	Non-HC	Ind. Dev.
Adj. R^2	0.516	0.510	0.514	0.570
N	37,337	29,279	67,713	24,471

This table reports OLS estimates of the effects of wildfire smoke pollution on municipal borrowing costs in the cross-section of county underinsurance per hospital. The dependent variable is offering yield spread (%), and the main independent variables are the interactions of *Smoke* with *Health* and the *Underins/Hosp* (*UndH*). *Smoke* is the standardized population-weighted cumulative amount of smoke PM_{2.5} exposure during the county-year. *UndH* is the standardized log average number of underinsured residents per hospital in that county. A resident is underinsured if they are uninsured, Medicaid-insured, or Medicare-insured. In columns (1) and (2), we use subsamples of counties with above-median and below-median *UndH*, respectively. In column (3), we use the full sample of counties and interact *UndH* with *Health*, *Smoke*, and *Health* $\times$ *Smoke*. 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 5: Wildfire Smoke Pollution, Underinsurance, and Medicaid Expansion

	(1) Yield Sp. (%)	(2) Yield Sp. (%)	(3) Yield Sp. (%)	(4) Yield Sp. (%)
<i>Smoke</i>	0.004 (0.010)	0.007 (0.006)	0.004 (0.009)	0.000 (0.016)
<i>Health</i> $\times$ <i>Smoke</i>	0.100*** (0.038)	0.103*** (0.035)	0.096** (0.037)	0.151*** (0.055)
<i>Smoke</i> $\times$ <i>UndH</i>	0.004 (0.004)	-0.004 (0.003)	0.003 (0.004)	-0.010 (0.007)
<i>Health</i> $\times$ <i>Smoke</i> $\times$ <i>UndH</i>	0.063*** (0.024)	-0.010 (0.034)	0.072*** (0.023)	0.126*** (0.033)
<i>MedExp</i> $\times$ <i>Smoke</i>			0.006 (0.012)	0.027 (0.024)
<i>Health</i> $\times$ <i>MedExp</i> $\times$ <i>Smoke</i>			0.006 (0.048)	0.003 (0.066)
<i>MedExp</i> $\times$ <i>Smoke</i> $\times$ <i>UndH</i>			-0.001 (0.005)	0.001 (0.010)
<i>Health</i> $\times$ <i>MedExp</i> $\times$ <i>Smoke</i> $\times$ <i>UndH</i>			-0.080** (0.038)	-0.136*** (0.042)
Controls	Yes	Yes	Yes	Yes
State-YM FE	Yes	Yes	Yes	Yes
Rating-YM FE	Yes	Yes	Yes	Yes
Insured-YM FE	Yes	Yes	Yes	Yes
Callable-YM FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Period	NoExp	PostExp	Full	Full
Baseline	Non-HC	Non-HC	Non-HC	Ind. Dev.
Adj. R^2	0.511	0.496	0.515	0.570
N	43,746	23,604	67,713	24,471

This table reports OLS estimates of the effects of wildfire smoke pollution on municipal borrowing costs as functions of underinsurance and Medicaid expansion. The dependent variable is offering yield spread (%), and the main independent variables are *Smoke* and its interactions with *Health*, *Underins/Hosp* (*UndH*), and *MedExp*. *Smoke* is the standardized population-weighted cumulative amount of smoke PM_{2.5} exposure during the county-year. *UndH* is the standardized log average number of underinsured residents per hospital in that county. *MedExp* is an indicator variable that equals one after the state expands Medicaid coverage under the ACA. In columns (1) and (2), we use subsamples of county-years in which the state has not expanded Medicaid and has expanded Medicaid, respectively. In column (3), we use the full sample of counties and interact *Health* $\times$ *Smoke* with *UndH* and *MedExp*. In column (4), we repeat the test in column (3), except that we use only industrial development bonds as the control group. 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 6: In-State Smoke, Out-of-State Smoke, and Healthcare Borrowing Costs

	(1) Yield Sp. (%)	(2) Yield Sp. (%)	(3) Yield Sp. (%)	(4) Yield Sp. (%)
<i>AwaySmoke</i>	0.000 (0.005)	0.009 (0.011)	-0.002 (0.005)	0.013 (0.011)
<i>Health</i> $\times$ <i>HomeSmoke</i>	0.106*** (0.033)	0.157*** (0.045)	0.116*** (0.036)	0.165*** (0.051)
<i>Health</i> $\times$ <i>AwaySmoke</i>	0.073** (0.029)	0.122*** (0.041)	0.105*** (0.031)	0.149*** (0.045)
<i>HomeSmoke</i> $\times$ <i>UndH</i>			0.001 (0.004)	-0.015 (0.010)
<i>Health</i> $\times$ <i>HomeSmoke</i> $\times$ <i>UndH</i>			0.079** (0.036)	0.117*** (0.044)
<i>AwaySmoke</i> $\times$ <i>UndH</i>			0.005 (0.004)	-0.011 (0.008)
<i>Health</i> $\times$ <i>AwaySmoke</i> $\times$ <i>UndH</i>			0.046* (0.023)	0.090*** (0.032)
Controls	Yes	Yes	Yes	Yes
State-YM FE	Yes	Yes	Yes	Yes
Rating-YM FE	Yes	Yes	Yes	Yes
Insured-YM FE	Yes	Yes	Yes	Yes
Callable-YM FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Baseline	Non-HC	Ind. Dev.	Non-HC	Ind. Dev.
Adj. R^2	0.508	0.556	0.509	0.557
N	64,311	21,859	64,252	21,854

This table reports OLS estimates of the effects of predicted in-state and out-of-state wildfire smoke on municipal borrowing costs. The dependent variable is offering yield spread (%), and the main independent variables are the interactions of *HomeSmoke* and *AwaySmoke* with *Health*. *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. Column (1) uses all non-healthcare bonds as the baseline group, and column (2) uses only industrial development bonds as the baseline group. In columns (3) and (4), we repeat the same tests, except that we also include *UndH* and its interactions with *HomeSmoke*, *HomeSmoke* $\times$ *Health*, *AwaySmoke*, and *AwaySmoke* $\times$ *Health*. 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 7: Wildfire Smoke and ER Visits

Panel A: Adult and Pediatric ER Visits				
	(1) $\ln(\text{ER})$	(2) $\ln(\text{ER}_{und})$	(3) $\ln(\text{ER}_{priv})$	(4) $\ln(\text{ER}_{und}/\text{ER}_{priv})$
<i>Smoke</i>	0.009** (0.004)	0.008** (0.004)	0.008* (0.004)	-0.000 (0.004)
Ins. Type	Any	Underins.	Private	Any
State FE	Yes	Yes	Yes	Yes
Year-Qt. FE	Yes	Yes	Yes	Yes
Adj. R^2	0.997	0.996	0.993	0.887
N	1,228	1,228	1,228	1,228
Panel B: Pediatric ER Asthma Visits				
	(1) $\ln(\text{ER})$	(2) $\ln(\text{ER}_{und})$	(3) $\ln(\text{ER}_{priv})$	(4) $\ln(\text{ER}_{und}/\text{ER}_{priv})$
<i>Smoke</i>	0.053*** (0.015)	0.050*** (0.015)	0.056*** (0.018)	-0.006 (0.011)
Ins. Type	Any	Underins.	Private	Any
State FE	Yes	Yes	Yes	Yes
Year-Qt. FE	Yes	Yes	Yes	Yes
Adj. R^2	0.986	0.980	0.972	0.767
N	1,228	1,227	1,227	1,227

This table reports OLS estimates of the effect of wildfire smoke pollution on total state-quarter ER visits by insurance type from 2010 to 2019. Panel A focuses on all adult and pediatric ER visits, and Panel B focuses on pediatric asthma ER visits. The dependent variable is the natural log of state-quarter ER visits. ER_{und} represents ER visits from underinsured patients. ER_{priv} represents ER visits from privately-insured patients. *Smoke* is the standardized population-weighted cumulative amount of smoke $\text{PM}_{2.5}$ exposure during the state-year-quarter. Robust standard errors clustered by state are reported in parentheses. The stars *, **, ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 8: Hospital Financial Summary Statistics

	Mean	Median	P25	P75	SD
<i>Margin</i>	0.039	0.039	-0.000	0.082	0.082
$g(NFA)_{t+1}$	0.037	-0.012	-0.057	0.061	0.233
$g(NFA)_{t+2}$	0.087	-0.013	-0.094	0.128	0.421
<i>FinInv</i>	0.571	0.269	0.064	0.796	0.760
$g(SRev)$	0.037	0.033	-0.010	0.081	0.095
<i>OpInc</i>	0.218	0.161	-0.040	0.412	0.538
$\log(TRev)$	4.555	4.595	3.465	5.641	1.355
Observations	9,875				

This table reports summary statistics for hospital financial variables from the HCRIS database. *Margin* is the ratio of total hospital revenue minus total hospital expense to total hospital expense. $g(NFA)_{t+1}$ and $g(NFA)_{t+2}$ are percentage change in hospital net fixed assets from year t to $t + 1$ and $t + 2$, respectively. *FinInv* is the ratio of financial investment value to net fixed assets in the previous year. $g(SRev)$ is one-year growth in service revenue from year $t - 1$ to t . *OpInc* is the operating income ratio to the previous year's net fixed assets. $\log(TRev)$ is the natural log of total revenue.

Table 9: The Effect of Smoke Pollution on Hospital Investment

	(1) $g(NFA)_{t+2}$	(2) $g(NFA)_{t+2}$	(3) $g(NFA)_{t+1}$	(4) $g(NFA)_{t+1}$
<i>Smoke</i>	-0.048** (0.021)	-0.047** (0.021)	-0.014 (0.009)	-0.014 (0.009)
<i>Smoke</i> $\times$ <i>UndH</i>		0.014 (0.011)		0.009 (0.005)
Hospital Controls	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes
Adj. R^2	0.247	0.247	0.094	0.095
N	9,368	9,368	9,241	9,241

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 ($g(NFA)_{t+2}$), and in columns (3) and (4), the dependent variable is the one-year percentage change in net fixed assets ($g(NFA)_{t+1}$). In columns (2) and (4), we interact *Smoke* with *UndH*, the standardized log average number of underinsured residents per hospital in that county. *Smoke* is the standardized population-weighted cumulative amount of smoke PM_{2.5} exposure during the county-year. The hospital and county control variables are described in the main text. Robust standard errors clustered by county are reported in parentheses. The stars *, **, ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 10: The Effect of Smoke Pollution on Hospital Profit Margins

	(1) <i>Margin</i>	(2) <i>Margin</i>	(3) <i>Margin</i>	(4) <i>Margin</i>
<i>Smoke</i>	0.015 (0.016)	0.017 (0.015)	0.013 (0.015)	0.016 (0.015)
<i>Smoke</i> $\times$ <i>UndH</i>			-0.024*** (0.009)	-0.028*** (0.009)
Hospital Controls	Yes	Yes	Yes	Yes
County Controls	No	Yes	No	Yes
State-Year FE	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes
Adj. R^2	0.714	0.714	0.714	0.714
N	9,381	9,320	9,381	9,320

This table reports OLS estimates on the effects of wildfire smoke pollution on hospital profit margin (*Margin*). *Margin* is the standardized ratio of total hospital revenue minus total hospital expense to total hospital expense. *Smoke* is standardized population-weighted cumulative wildfire-smoke PM_{2.5} exposure during the county-year. In columns (3) and (4), we interact *Smoke* with *UndH*, the standardized log average number of underinsured residents per hospital in that county. Columns (2) and (4) include the county-level controls from our baseline regression model. All specifications include state-by-year and hospital fixed effects. Robust standard errors clustered by county are reported in parentheses. The stars *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

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

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

August 31, 2026

INTERNET APPENDIX

This Appendix provides supplemental discussions and 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; telephone: (773) 964-3936) 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 Manuel Adelino, Effi Benmelech, Stephen Billings, Dan Garrett, Gustavo Grullon, Christoph Herpfer, Matthew Kahn, Wen-Chi Liao, Brian McCartan, Gary Painter, Robert Parrino, Adam Sacarny, Frederik Strabo, Fabrice Tourre, Sheng-Jun Xu, Tingyu Zhou, Qifei Zhu, and seminar and conference participants at the AREUEA 2025 National Conference, the Baruch/JFQA Climate Finance and Sustainability Conference, the 14th Annual Brookings Municipal Finance Conference, Chapman University, Dalhousie University, the Federal Reserve Bank of Chicago, the 2025 FIRS Conference, the 2024 FMA International Emerging Scholars Initiative, the 2025 NFA Conference, the 2025 pre-WFA Summer Real Estate Research Symposium, the University of Cincinnati, the University of Illinois Chicago, the University of Memphis, the University of Texas at San Antonio, the Yale Municipal Research Conference, Villanova University, 20th North American Meeting of the Urban Economics Association, and the University of Wisconsin–Madison for helpful comments. We thank Dylan Ryfe for excellent research assistance. We affirm that we have no material financial interests related to this research. 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. Literature on Health Effects

We discuss the literature on wildfire smoke pollution on physical and mental health. Wildfire smoke contains a complex mixture of toxic fine particulate matter ($\text{PM}_{2.5}$), carbon monoxide, volatile organic compounds, and other toxic pollutants. $\text{PM}_{2.5}$ is particularly harmful because it penetrates deep into the respiratory tract, enters the bloodstream, and causes acute respiratory conditions such as asthma and bronchitis.

A growing literature documents that wildfire smoke significantly increases hospital utilization. Deryugina et al. (2019) find that wildfire smoke increases emergency room visits for respiratory and cardiovascular conditions. Aguilera et al. (2021) show that wildfire smoke has stronger health effects than $\text{PM}_{2.5}$ from other sources, and that an increase in wildfire-specific $\text{PM}_{2.5}$ is associated with an increase in respiratory hospitalizations. Heft-Neal et al. (2023) document increases in hospital admissions during smoke events across multiple US regions.

Unlike one-time natural disasters that cause physical destruction, wildfire smoke exposure is recurrent and seasonal in many regions. Recent decades have seen substantial increases in the frequency and intensity of wildfire smoke days (Childs et al., 2025). First Street (2024) projects that the number of individuals exposed to unhealthy smoke days will rise substantially over the next 30 years. Because smoke events are recurring and trending upward, healthcare systems may face persistent demand pressures rather than one-off shocks. Qiu et al. (2025) project that smoke $\text{PM}_{2.5}$ could result in 71,420 excess deaths per year by 2050 under a high-warming scenario, which represents a 73% increase relative to the estimated annual average from 2011 to 2020. Clausen, Knittel and Wolfram (2025) show that the per-household cost of deaths attributable to wildfire smoke averages between \$65 and \$100.

The medical literature establishes that wildfire smoke increases emergency department visits and hospital admissions across multiple regions and patient groups. These effects occur without corresponding changes in local fiscal capacity or infrastructure since smoke can travel across state borders and affect areas with no direct wildfire damage. Accordingly, wildfire smoke represents a demand-side health shock that can affect hospital operations and resource allocation. Our analysis builds on this evidence by examining whether financial markets incorporate these documented health effects into the healthcare cost of capital and subsequent investment activity.

Appendix A.2. Robustness Tests

We first show that direct physical damages from wildfires do not affect our baseline results from the OLS regression model in equation (1) of the main text. In particular, in columns (1) 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, the exclusion of California, where a significant percentage of wildfires occurred during our sample period, and the joint exclusion of California and any county-year in which at least one wildfire occurred.

In Table A.2, we further show that our baseline results are unaffected when we use alternative constructions of the yield spread, consider only the post-summer months of the year, or use a 12-month moving average of *Smoke*. 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 (ex-

cluding 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 callability, 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. In column (3), we retest our baseline regression model using only issues from the fourth quarter of the year when the wildfire season has largely concluded, and find similar results. In columns (4) and (5), we use a standardized 12-month moving average of *Smoke* (*SmokeMA*), and find similar effects on the healthcare offering yield spread and the healthcare secondary yield, respectively.

Appendix A.3. Externalities

We discuss and analyze whether the *AwaySmoke* effects documented in Section IV.D should be classified as cross-state negative externalities or spillovers. From a prevention perspective, related research supports the “externality” classification. In the case of California, the California Council on Science and Technology (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, 2026), and about \$155 million in funds that were meant for community protection and wildland fuel reduction.

We provide evidence that wildfire prevention expenditures are significantly lower in California compared to other states. In particular, we collect panel data on wildfire prevention expenditures from the USDA Forest Service, including information on all activities and costs of reducing hazardous fuel treatment on federal lands. Using these data, we calculate the state-year wildfire prevention expenditure per acre (*Prevention/Acre*). Our regression results in columns (1) and (2) of Table A.3 indicate that California spends about \$334 less on wildfire prevention per acre, compared to an average of approximately \$365 per acre in the remaining states, even after controlling for the number of wildfires and the number of structures damaged in the state.

We also provide evidence that California spends more on wildfire suppression than other states, perhaps due to its relative lack of spending on wildfire prevention. We collect panel data on wildfire suppression expenditures from ten Western US state agencies that oversee wildfire suppression efforts (Cook and Becker, 2017). Using these data, we calculate the state-year expenditure on wildfire suppression per burned acre (*StateSuppr/Acre*), and state-year federal expenditure on wildfire suppression per burned acre (*FedSuppr/Acre*). Our regression results in columns (3) and (4) of Table A.3 indicate that California spends about \$9,236 on wildfire suppression per burned acre, compared to an average of \$680 per burned acre in the remaining states. Related findings in columns (5) and (6) indicate that the federal government pays California about \$613 per burned acre for suppression efforts, compared to an average of \$325 in the remaining states. Given the relatively low spending on prevention and high expenditure on suppression, these results suggest states should establish a minimum threshold for prevention-to-suppression expenditures, similar to post-disaster spending

requirements from FEMA (Wara et al., 2020).

Table A.1: Robustness Tests for Baseline Regressions

	(1) Yield Sp. (%)	(2) Yield Sp. (%)	(3) Yield Sp. (%)	(4) Yield Sp. (%)
<i>Smoke</i>	0.007 (0.006)	-0.004 (0.007)	-0.001 (0.008)	-0.004 (0.009)
<i>Health</i> $\times$ <i>Smoke</i>	0.067*** (0.025)	0.070*** (0.026)	0.073*** (0.026)	0.078*** (0.028)
Controls	Yes	Yes	Yes	Yes
State-YM FE	Yes	Yes	Yes	Yes
Rating-YM FE	Yes	Yes	Yes	Yes
Insured-YM FE	Yes	Yes	Yes	Yes
Callable-YM FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Model	Fire Control	Fire Excluded	CA Excluded	Fire/CA Excl.
Adj. R^2	0.514	0.510	0.507	0.508
N	67,780	64,512	63,292	61,397

We retest our baseline regression model in equation (1) of the main text with the following modifications: in column (1), we include the county-year number of wildfire events as a control variable; in column (2), we instead exclude any county-year that experienced a wildfire event; in column (3), we exclude all counties in the state of California; and in column (4), we apply the exclusions in columns (2) and (3). 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) <i>y</i> (Tax Adj.)	(2) <i>y</i> (Call Adj.)	(3) Yield Sp.	(4) Yield Sp.	(5) Yield Sp.
<i>Smoke</i>	0.021* (0.012)	0.008 (0.007)	0.012 (0.011)		
<i>Health</i> $\times$ <i>Smoke</i>	0.126*** (0.044)	0.057** (0.026)	0.081** (0.030)		
<i>SmokeMA</i>				0.014** (0.006)	-0.020*** (0.007)
<i>Health</i> $\times$ <i>SmokeMA</i>				0.058** (0.028)	0.059*** (0.021)
Controls	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes
Rating-Year FE	Yes	Yes	Yes	Yes	Yes
Insured-Year FE	Yes	Yes	Yes	Yes	Yes
Callable-Year FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	No
Bond FE	No	No	No	No	Yes
Model	Tax Adj.	Call Adj.	Q4	SmokeMA	SmokeMA
Sample	OffMkt	OffMkt	OffMkt	OffMkt	SecMkt
Adj. R^2	0.631	0.487	0.513	0.514	0.806
N	67,069	67,780	24,050	67,780	7,763,120

We retest our baseline regression model in equation (1) of the main text 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 use a subsample of bonds issued in the last quarter of each year; in column (4), we use the standardized 12-month moving average of smoke pollution; in column (5), we repeat the test in column (4), except that we use secondary yield spread instead of offering yield spread, and use bond fixed effects instead of county fixed effect. Robust standard errors clustered by county and year-month are reported in parentheses. The stars *, **, ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.3: Fire Prevention and Suppression Expenditures

	(1) Prevention/Acre	(2) Prevention/Acre	(3) StateSuppr/Acre	(4) StateSuppr/Acre	(5) FedSuppr/Acre	(6) FedSuppr/Acre
$\mathbf{1}_{CA}$	-333.67*** (79.93)	-344.23*** (110.09)	8555.68*** (2380.79)	30106.22*** (7428.03)	287.86* (155.31)	1514.87*** (376.57)
$N(\text{Fires})$		0.17 (0.17)		-121.66*** (38.09)		-7.89*** (2.50)
$\mathbf{1}_{CA} \times N(\text{Fires})$		-0.18 (0.17)		-0.61 (2.08)		0.82 (1.75)
$N(\text{Str. Damaged})$		0.00 (0.01)		-3.87** (1.65)		0.80 (0.49)
$\mathbf{1}_{CA} \times N(\text{Str. Dmg.})$		-0.00 (0.01)		-1.55** (0.64)		-1.01** (0.48)
Constant	365.25*** (79.89)	395.25*** (109.63)	679.98*** (130.06)	764.79*** (205.55)	324.67*** (78.83)	296.17*** (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 differences in wildfire prevention and suppression spending between California and other Western US states using OLS regressions. The dependent variables used in these regressions are annual expenditure on fire prevention per acre in columns (1) and (2), state expenditure on fire suppression per burned acre in columns (3) and (4), and state-specific federal expenditure per burned acre in 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.

Appendix References

- Aguilera, Rosana, Thomas Corringham, Alexander Gershunov, and Tarik Benmarhnia.** 2021. “Wildfire smoke impacts respiratory health more than fine particles from other sources: observational evidence from Southern California.” *Nature Communications*, 12(1): 1493.
- Baylis, Patrick, and Judson Boomhower.** 2026. “Mandated versus voluntary adaptation to natural disasters: The case of US wildfires.” *Journal of Political Economy*, 134(3): 895–948.
- 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>.
- Childs, Marissa, Mariana Martins, Andrew Wilson, Minghao Qiu, Sam Heft-Neal, and Marshall Burke.** 2025. “Growing Wildfire-Derived PM_{2.5} Across the Contiguous US and Implications for Air Quality Regulation.” Working paper, University of Washington.
- Clausing, Kimberly A, Christopher R Knittel, and Catherine Wolfram.** 2025. “Who Bears the Burden of Climate Inaction?” *Brookings Papers on Economic Activity*, 2025(1): 371–461.
- 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.
- 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.
- First Street.** 2024. “Atrocious Air.” Retrieved at: <https://firststreet.org/research-library/atrocious-air>.
- 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.
- 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.

- 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.
- Qiu, Minghao, Jessica Li, Carlos F Gould, Renzhi Jing, Makoto Kelp, Marissa L Childs, Jeff Wen, Yuanyu Xie, Meiyun Lin, Mathew V Kiang, et al.** 2025. “Wildfire smoke exposure and mortality burden in the USA under climate change.” *Nature*, 647(8091): 935–943.
- 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.