

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 November 2026)

Research Department

https://doi.org/10.24149/wp2503r2

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: November 10, 2026

Abstract

We show that persistent wildfire smoke pollution significantly increases healthcare municipal borrowing costs. Consistent with smoke increasing relative demand from underinsured patients, we find that the effect is concentrated in high-underinsurance areas. Evidence from staggered state-level Medicaid expansions shows that greater insurance coverage mitigates the smoke effect on healthcare borrowing costs. Hospital-level tests show that smoke reduces investment growth and reduces profitability in high-underinsurance areas. Out-of-state wildfire smoke similarly increases healthcare borrowing costs, indicating that wildfires impose negative externalities on other states. Our results indicate that climate risk pricing is not necessarily tied to physical damages from local climate events.

JEL Classification: G12, H74, I11, I13, Q53, 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, telephone: (312) 355-8215.

‡Dermot Murphy, College of Business, University of Illinois Chicago, murphyd@uic.edu, telephone: (312) 355-4372.

§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, telephone: (775) 682-7235.

I. Introduction

The proliferation of wildfires around the globe has significantly affected local economies 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).

The adverse consequences of wildfires extend well beyond the immediate burn zones. Wildfires produce drifting smoke plumes that travel hundreds of miles and increase the volume of airborne toxic fine particulate matter ($PM_{2.5}$) (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). Wildfire smoke is now responsible for about 20% of global $PM_{2.5}$ exposure, and almost 50% of $PM_{2.5}$ exposure in the Western US (UNEP, 2022).

Hospitals have naturally absorbed much of the increased demand for healthcare services stemming from wildfire smoke exposure. However, the financial consequences are not immediately clear because hospitals, unlike most other firms, cannot perfectly ration services and accept only profitable customers.[1] Instead, hospitals act as insurers of last resort for patients who cannot pay (Garthwaite, Gross and Notowidigdo, 2018), and thus the resulting cash flows depend on local insurance coverage. Building on this insight, we provide a novel study of how wildfire smoke 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 mor-

[1] Privately 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 US hospitals from turning away underinsured 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).

tality rates (Aghamolla et al., 2024). Furthermore, because of the long-distance nature of wildfire smoke, our study addresses the broader question of 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 about issuer solvency. This market also represents a primary source of financing for nonprofit hospitals, which comprise the majority 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.

Using a novel panel of wildfire smoke data from the Stanford Echo Lab, we analyze the effect of wildfire smoke pollution on yields in the healthcare municipal bond market relative to the non-healthcare market. Because bond yields are forward-looking, we decompose smoke exposure into two components: *ExpSmoke*, the county's expected exposure based on its history of persistent smoke (the average over the three preceding years), and *InnovSmoke*, the deviation of current exposure from that expectation. In the offering market, identification comes from comparing healthcare and non-healthcare bonds with similar smoke exposure, and otherwise similar healthcare bonds with different exposure. In the secondary market, identification comes from within-bond changes in healthcare yields relative to non-healthcare yields as a county's smoke exposure changes.

We find that wildfire smoke pollution is associated with a significantly higher cost of capital for healthcare borrowers, and that the market mainly prices the expected component of smoke exposure. A one standard deviation increase in *ExpSmoke* is associated with a 12.0 basis point

(bps) increase in the average offering yield spread for healthcare municipal bonds relative to non-healthcare municipal bonds, whereas a one standard deviation increase in *InnovSmoke* is associated with a statistically insignificant 2.0 bps increase. The 12.0 bps effect represents 10% of the average healthcare yield spread and is comparable to the borrowing cost effect due to sea level rise in Goldsmith-Pinkham et al. (2023) (9%). Our findings are robust to $Health\times$ Year-Month fixed effects, which absorb healthcare-wide shocks such as the 2012 Supreme Court ruling on the Affordable Care Act (Gao, Lee and Murphy, 2022). Our findings are also robust to State $\times$ Year-Month or County $\times$ Year-Month fixed effects, controls for local wildfire damage, and the exclusion of California. Within-bond yield changes in the secondary market similarly show that a one standard deviation increase in *ExpSmoke* increases healthcare secondary yield spreads by 12.0 bps relative to non-healthcare bonds, while *InnovSmoke* has a small and insignificant effect. Using the dynamic smoke model in Borgschulte, Molitor and Zou (2022), we further find that future smoke is not associated with current secondary yields, suggesting that healthcare yields do not trend differentially ahead of smoke exposure.

The effect of wildfire smoke exposure on healthcare borrowing costs is more pronounced in counties with more underinsured residents per hospital ($Underins/Hosp$). We define individuals as underinsured if they are uninsured, Medicaid-insured, or Medicare-insured; these groups are associated with negative hospital profit margins (Wilson and Cutler, 2014). The *ExpSmoke* effect is 45% stronger if $Underins/Hosp$ is one standard deviation above its mean. By contrast, non-healthcare borrowing costs are unaffected by expected wildfire smoke, including those in high-underinsurance counties. These findings support our proposed mechanism that smoke exposure increases healthcare credit risk through the insurance channel.

The staggered state-level expansion of Medicaid eligibility under the Affordable Care Act

sharpens identification of the insurance channel because it moved many uninsured residents into Medicaid and reduced hospitals' uncompensated care costs (Dranove, Garthwaite and Ody, 2016; Gao, Lee and Murphy, 2022). Following the same healthcare bonds in the secondary market, we find that after a state expands Medicaid, the sensitivity of healthcare yields to *ExpSmoke* is significantly attenuated in high-uninsurance counties. This decline is not explained by fixed differences between expansion and non-expansion states or by changes common to all states after 2014. Event study estimates show no differential trend in the years prior to expansion, and a decline that persists after expansion. The results also hold when we compare only states that expanded in January 2014 to states that had not expanded by 2019.

Wildfire smoke also increases borrowing costs for hospitals in nearby states. Using wildfire data from the US Department of Homeland Security (DHS), we separate smoke into the components attributable to in-state and out-of-state wildfires (*HomeSmoke* and *AwaySmoke*). We find that the effect of expected *AwaySmoke* on healthcare borrowing costs (11.6 bps per standard deviation) is statistically similar to that of expected *HomeSmoke* (15.1 bps), and that both effects are stronger when the underinsurance rate is high. These results indicate that expected smoke from other states is an important driver of healthcare credit risk.

ER data from the Agency for Healthcare Research and Quality (AHRQ) confirm that smoke increases demand for healthcare services. We find that a one standard deviation increase in expected quarterly smoke exposure raises ER visits from underinsured and privately insured patients by 1.7% and 1.3%, respectively, and that smoke innovations raise ER visits as well. Underinsured discharges outnumber privately insured discharges by about three to one. If a hospital discharges 15,000 underinsured patients and 5,000 privately insured patients per quarter, for example, then a one standard deviation increase in expected smoke exposure would generate another

$15,000 \times 1.7\% = 255$ underinsured quarterly discharges and $5,000 \times 1.3\% = 65$ privately insured quarterly discharges.

If smoke raises healthcare credit risk by increasing expected unprofitable demand for healthcare services, then its effects should also appear in hospitals' own financial statements. We regress hospital profit margin and fixed asset growth on *ExpSmoke* and *InnovSmoke* and their interactions with $Underins/Hosp$. We find that both components of smoke are associated with lower profit margins in high-underinsurance counties. In particular, a one standard deviation increase in *ExpSmoke* (*InnovSmoke*) is associated with a 2.9% (3.2%) reduction in the standardized profit margin if $Underins/Hosp$ is also one standard deviation above its mean. We also find that expected smoke is associated with lower hospital investment growth, in that a one standard deviation increase in *ExpSmoke* is associated with a 2.4 percentage point reduction in one-year investment growth. By contrast, *InnovSmoke* has no significant effect on investment growth. Like bond investors, hospitals therefore appear to respond to persistent smoke exposure, but not to residual fluctuations which hospitals likely view as temporary. These results indicate that the adverse financial effects from smoke-driven demand shocks translate into adverse real effects in the form of reduced investment.

Our study builds on the literature on climate finance. Recent studies show that municipal bond yields reflect physical climate risks from rising sea levels (Painter, 2020; Goldsmith-Pinkham et al., 2023) and direct wildfire damages (Jeon, Barrage and Walsh, 2025). Additional studies focus on the perceived risk of physical property damage (e.g., Baldauf, Garlappi and Yannelis, 2020; Auh et al., 2022; Bakkensen and Barrage, 2022; Nguyen et al., 2022; 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*; Garnache, 2026), perceived cancer risk from toxic plants and its effect on local

real estate prices (van Binsbergen et al., 2026), or local attention to climate change and its effects on households and firms (Kostovetsky et al., 2026). Closest to our setting, Acharya et al. (2022) show that exposure to heat stress, which also does not damage physical property, raises municipal bond yields. However, wildfire smoke differs because it imposes a sector-specific cost, in that it raises demand for emergency care that hospitals must provide regardless of patients' ability to pay.[2] Comparing healthcare and non-healthcare bonds in the same county and month therefore absorbs local economic shocks (e.g., reduced consumption and economic activity) that affect all issuers, and allows us to link the borrowing cost effects to insurance coverage and Medicaid expansion. Wildfire smoke also travels far from the fires that produce it (often across state lines), and thus the healthcare borrowing cost effects can fall on jurisdictions that have no control over the land management decisions behind those fires.

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 health-

[2]Internet Appendix A.1 reviews the medical and epidemiological literature on wildfire smoke exposure, hospital utilization, and health outcomes.

care 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). Cornaggia, Li and Ye (2026) show that the rise of high-deductible health plans makes hospital revenues more procyclical by reducing insurance risk sharing, which complements our evidence that insurance coverage shapes hospitals' exposure to external demand shocks.

II. Conceptual Framework

Apart from relatively minor costs such as corrosion and filter replacement, smoke from distant wildfires leaves hospital property intact, and its effect on any single hospital is largely diversifiable for bond investors. Smoke should therefore matter for healthcare borrowing costs mainly because it changes the expected cash flows that secure the debt. In this section, we develop a simple cash-flow framework built on the premise that US hospitals must treat emergency patients regardless of ability to pay. The framework delivers a set of testable predictions, which we take to the data in Sections IV and V.

A. *Smoke as a Demand Shock*

Under the Emergency Medical Treatment and Labor Act (EMTALA), hospitals with emergency departments must screen and stabilize every patient who seeks emergency care, regardless of insurance status (U.S. Dept. of Health and Human Services, 2024). Hospitals therefore act as "insurers of last resort" for the uninsured. Garthwaite, Gross and Notowidigdo (2018) show that hospital uncompensated care costs rise nearly one-for-one with the local uninsured population. Because smoke-related respiratory and cardiovascular visits arrive through the emergency department (Deryugina et al., 2019; Heft-Neal et al., 2023), a smoke event is a demand shock that hospitals cannot perfectly ration, and the associated profit margin depends on the incremental patient mix.

Consider a hospital that finances itself with a bond secured by its operating cash flow. Patients belong to payer groups $j \in \{P, M, D, U\}$ (private insurance, Medicare, Medicaid, and uninsured), with volume shares s_j and profit margins m_j. Operating cash flow is as follows:

$$C = Q \sum_j s_j m_j - F, \tag{1}$$

where Q is the total patient volume and F is the fixed operating cost. Smoke-related visits arrive through the emergency department. The associated payer mix s_j^{ER} and margins m_j^{ER} differ from the hospital average, as uninsured and Medicaid patients account for a disproportionate share of ER visits (Tang et al., 2010), and uninsured ER care is largely uncompensated (Wilson and Cutler, 2014; Hsia, Kellermann and Shen, 2011). A smoke shock (*Smoke*) raises emergency volume Q^{ER} proportionally across payer groups, $\Delta Q^{ER}/Q^{ER} = \beta \cdot Smoke$, which is consistent with our later evidence that smoke raises ER visits by similar percentages for underinsured and privately insured

patients. The change in cash flow is therefore:

$$\Delta C = \beta \cdot Smoke \cdot Q^{ER} \cdot \bar{m}, \qquad \bar{m} \equiv \sum_j s_j^{ER} m_j^{ER}. \tag{2}$$

The sign and size of the cash flow effect are governed by the margin on incremental ER visits, $\bar{m}$. Privately insured patients carry positive margins, Medicare and Medicaid margins carry somewhat negative margins, and uninsured care is largely uncompensated, such that $m_U^{ER} < 0$. Because s_U^{ER} exceeds the hospital-wide uninsured share and ER margins are at or below hospital-wide margins, $\bar{m}$ can be negative even when the hospital's average margin is positive. Holding the shock fixed, ΔC is more negative where the uninsured share is higher.

B. Mapping Cash Flows to Yields

We view the bond price through the lens of a structural credit model (Merton, 1974; Leland, 1994). The bond defaults when cash flow falls below required debt service, so the credit spread is a decreasing and convex function of the hospital's distance to default. Default risk is an economically important component of municipal yield spreads (Schwert, 2017), and it is especially relevant for bonds in the healthcare sector, where defaults are more common than in other sectors (Gao, Lee and Murphy, 2019).

Investors price the present value of expected future smoke costs. Let $\theta_{c,t-1}$ denote investors' belief about the expected smoke exposure of county c entering period t, formed from the county's smoke history. After observing $Smoke_{ct}$, investors update $\theta_{ct} = \theta_{c,t-1} + \kappa(Smoke_{ct} - \theta_{c,t-1})$ with $\kappa \in [0,1]$. Combining this updating rule with equation (2), the value of pledged cash flows is

approximately:

$$V_{ct} \approx V_c^0 + \beta\, Q^{ER} \bar{m}\, [\theta_{c,t-1} + \kappa\, (Smoke_{ct} - \theta_{c,t-1})]\, A(r,T), \tag{3}$$

where $A(r,T)$ is an annuity factor over the remaining life of the bond. Because expected exposure applies to every remaining year of the bond, a modest annual cash flow effect stemming from a modest increase in unprofitable demand for healthcare services can support a large change in bond value, in the same way that expected future sea-level or disaster exposure is capitalized into prices (Bernstein, Gustafson and Lewis, 2019; Painter, 2020; Goldsmith-Pinkham et al., 2023). A smoke innovation changes bond value by changing beliefs about future exposure. Formally, holding the other smoke component fixed, we have that $\partial V_{ct}/\partial \theta_{c,t-1} = \beta Q^{ER} \bar{m} A(r,T)$ and $\partial V_{ct}/\partial (Smoke_{ct} - \theta_{c,t-1}) = \kappa \beta Q^{ER} \bar{m} A(r,T)$, meaning that the price effect of a smoke innovation is a fraction κ of the price effect of expected exposure. If annual smoke realizations are noisy relative to a county's underlying exposure such that κ is small, yield spreads should load mainly on expected exposure ($\theta_{c,t-1}$) and less on current-year smoke innovations ($Smoke_{ct} - \theta_{c,t-1}$). Hospital operating outcomes, by contrast, may respond to both expected smoke and realized smoke since the demand effects stemming from smoke exposure are contemporaneous. We therefore decompose *Smoke* into *ExpSmoke* (a proxy for $\theta_{c,t-1}$) and $InnovSmoke = Smoke - ExpSmoke$ in all of our tests.

C. Predictions

Our framework yields the following predictions, each of which we test in the remainder of the paper:

Prediction 1 (Healthcare-specific pricing). Smoke exposure raises yield spreads on healthcare bonds relative to non-healthcare bonds in the same county if $\bar{m} < 0$. The effect operates mainly through the expected exposure (*ExpSmoke*) channel if κ is small.

Prediction 2(a) (Payer mix). The effect of smoke exposure on healthcare yield spreads is larger where underinsured patients account for a larger share of hospital demand ($\bar{m}$ is lower).

Prediction 2(b) (Insurance coverage). Medicaid expansion moves patients from the uninsured group into Medicaid (increasing $\bar{m}$). It should therefore weaken the sensitivity of healthcare yield spreads to smoke exposure, especially in high-uninsurance counties.

Prediction 3 (Real effects). Hospital profit margins should decrease with both expected and unexpected smoke since realized smoke drives realized demand. Hospitals should also reduce investment activity since investment is sensitive to internal cash flows (Adelino, Lewellen and Sundaram, 2015).

D. Relation to Prior Work

Our framework provides context for how our setting differs from two closely related studies. Cornaggia et al. (2022) show that the opioid crisis worsens municipal finance outcomes; in their setting, a local public health crisis erodes the tax base and the fiscal capacity of local governments. Our setting differs in two ways. First, by comparing healthcare and non-healthcare bonds within

the same economic region, we have that wildfire smoke operates through the hospital demand channel, and thus the borrowing cost effect depends on local insurance coverage rather than on the local economy. An implication is that underinsurance in the US can amplify the financial effects of public health shocks on hospitals. Second, the opioid crisis and most natural disasters impose their costs mainly in their immediate locations, whereas wildfire smoke travels across county and state lines. The financial costs of smoke therefore fall partly on regions that do not control the underlying fire risk, so wildfire mismanagement in one state can impose negative externalities on hospitals in other states.

Gao, Lee and Murphy (2022) show that the state-level expansion of Medicaid under the ACA reduces healthcare municipal borrowing costs on average. In contrast, we examine how insurance coverage changes the pass-through of smoke-induced demand to hospital credit risk. Our Medicaid tests control for any average change in healthcare yields after a state-level expansion of Medicaid, which is the effect studied by Gao, Lee and Murphy (2022). Our estimates therefore capture how the sensitivity of healthcare yields to expected smoke changes after expansion. The two sets of findings are complementary, and together imply that a rollback of Medicaid or Medicare funding could amplify the effects of wildfire smoke on hospital finances. More broadly, our results add to evidence that public health policies have real effects on firms (Gao et al., 2020).

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 classify bonds into two groups: (1) healthcare bonds, and (2) the remaining non-healthcare bonds. We exclude bonds issued by state governments and state-level conduit authorities, as these bonds are not tied to the credit profile or patient base of a single county. We also calculate the offering yield spread, the central outcome variable in our empirical analysis, by subtracting the coupon-equivalent risk-free rate from the offering yield.[3] Lastly, we aggregate our observations to the issue level: for issue size, we calculate the total size across bonds within each issue, and for the remaining variables, we calculate the size-weighted average across bonds within each issue.

Secondary yields come from the Municipal Securities Rulemaking Board (MSRB) Electronic Municipal Market Access (EMMA) database for 2010–2019. We compute the trade size-weighted average yield across customer buy transactions for each bond-year-month, exclude bonds with fewer than ten transactions, keep seasoned bonds outstanding for at least one year, and compute secondary yield spreads analogously.

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

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 bond 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 the contiguous US, where wildfire smoke pollution information is not available.

Table 1 reports summary statistics. Healthcare issues make up 5.3% of the sample by issue size and 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 spreads, higher ratings, smaller sizes, and shorter maturities, and are more likely to be general obligation or insured; our tests control for these differences.

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 cell and day, they calibrate the $PM_{2.5}$ predictions using: (1) distance to the closest fire clusters, (2) mean eastward wind speeds, (3) mean northward 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 boundary layer height, and (8) land use and elevation. As a result, the predicted $PM_{2.5}$ measure is designed to exclude the variation from non-wildfire factors such as industrial pollution, road density, dust, and elemental carbon (Childs et al., 2022).

We aggregate these predictions to obtain the population-weighted cumulative $PM_{2.5}$ exposure for each county, using 2014 ACS 5-year population shares. For the yield tests, we measure exposure over the 12 months ending in the month of each yield observation, so that the exposure window never extends beyond the pricing month. We refer to the standardized value of this measure as *Smoke*.

Because bond prices reflect expectations, we split this exposure into its expected and innovation components. *ExpSmoke* is the average of the county's exposure over the three preceding 12-month windows (ending 12, 24, and 36 months before the yield observation), and thus it uses only smoke observable at the pricing date. *InnovSmoke* is the 12-month exposure minus *ExpSmoke*. We winsorize each component at the 1st and 99th percentiles, and standardize each component using its mean and standard deviation. Expected exposure varies mainly across counties and with the secular rise in smoke, while innovations capture year-to-year changes. For the annual hospital tests, *ExpSmoke* is the average calendar-year exposure over the three preceding years, and for the quarterly ER tests it is the average exposure in the same quarter of the three preceding years. All of our regressions include both components.

Table 2 and Figure 1 show that smoke exposure has trended upward, with spikes in some years

that double the previous exposure. Figure 2 shows that exposure has shifted from the Midwest early in the decade toward the Western US later in the decade.

C. Hospital and Insurance Data

For our hospital-level tests, we use hospital-year financial data for 2012–2019 from the HCRIS database.[4] We also use county-level insurance coverage data from the Census Bureau's Small Area Health Insurance Estimates (SAHIE) and ACS, and state-quarter emergency department visits by expected payer from the Healthcare Cost and Utilization Project (HCUP) database.

IV. Wildfire Smoke and Healthcare Borrowing Costs

A. Baseline Tests

We compare the offering yield spreads of healthcare and non-healthcare municipal issues in the same county. The dependent variable is y_{ijt}, the offering yield spread for issue i in county j and year-month t, and the main independent variables are $ExpSmoke_{jt}$ and $InnovSmoke_{jt}$, the expected and unexpected components of the county's population-weighted cumulative smoke $PM_{2.5}$ exposure over the 12 months ending in year-month t (Section III). We estimate the following ordinary least squares (OLS) regression model:

[4]Processed HCRIS cost reports are available at `https://github.com/asacarny/hospital-cost-reports`. We thank Adam Sacarny for making this database publicly available.

$$
\begin{aligned}
y_{ijt} &= \beta_E^C \cdot ExpSmoke_{jt} + \beta_E^H \cdot ExpSmoke_{jt} \times Health_i \\
&+ \beta_I^C \cdot InnovSmoke_{jt} + \beta_I^H \cdot InnovSmoke_{jt} \times Health_i \\
&+ \gamma \cdot X_{ijt} + \delta \cdot Z_{jt} + \rho_j + \psi_{st} + \phi_{it} + \lambda_{ht} + \varepsilon_{ijt},
\end{aligned} \tag{4}
$$

where $Health$ equals one for healthcare issues. The coefficients β_E^H and β_I^H measure the incremental effects of *ExpSmoke* and *InnovSmoke* on healthcare yield spreads. The issue-level controls X are the natural logs of issue size and size-weighted maturity and indicators for general obligation and negotiated issues, and the county-level controls Z are 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, ψ_{st}, and ϕ_{it} are County, State $\times$ Year-Month, and $\{$Rating, Insured, Callable$\}$ $\times$ Year-Month fixed effects, where Rating is the average bond rating in the county. The latter control variables are interacted with Year-Month fixed effects because their yield effects can vary over time; for example, Cornaggia, Hund and Nguyen (2024) show that insurance is associated with lower yields in some years and higher yields in others. λ_{ht} are $Health\times$ Year-Month fixed effects, which absorb healthcare-wide shocks such as the decline in healthcare yields after the June 2012 Supreme Court ruling on the ACA (Gao, Lee and Murphy, 2022). Standard errors are double-clustered by county and year-month.

Table 3 reports the results. In column (1), we first omit ϕ_{it}, and find that a one standard deviation increase in *ExpSmoke* is associated with a 12.3 bps increase in the offering yield spread for healthcare issues relative to non-healthcare issues, whereas a one standard deviation increase in *InnovSmoke* is associated with a statistically insignificant 2.0 bps increase. Including ϕ_{it} in

column (2) yields similar estimates of 12.0 and 2.0 bps, and the difference between the two is statistically significant ($p = 0.005$). In column (3), we include County $\times$ Year-Month fixed effects to compare healthcare and non-healthcare bonds within the same county-year-month. The $Health \times ExpSmoke$ estimate rises to 23.2 bps, which may partly reflect the restricted sample's greater weight on populous counties with frequent issuance, while $Health \times InnovSmoke$ remains statistically insignificant. These findings indicate that the market prices expected wildfire smoke exposure as a credit risk for healthcare issuers, while year-to-year deviations from expected exposure have little effect on yields. Column (4) uses secondary yield spreads with bond fixed effects, which forces a within-bond comparison, and inverse weights observations by the number of county-month transactions so that high-volume county-months are not overrepresented. A one standard deviation increase in *ExpSmoke* raises relative healthcare secondary yield spreads by 12.0 bps, nearly identical to the offering market estimate, while the $Health \times InnovSmoke$ estimate is small and insignificant.

Internet Appendix Figure A.1 reports a visual robustness test that replaces *ExpSmoke* and *InnovSmoke* in column (4) with current 12-month *Smoke* and its 12-month and 24-month leads and lags (Borgschulte, Molitor and Zou, 2022). The lagged windows, which are the inputs to *ExpSmoke*, have larger effects on seasoned healthcare yields (5.1 and 4.3 bps) than current smoke (2.1 bps), which is consistent with yields responding to accumulated exposure. By contrast, the leads are small and insignificant (1.4 and -1.9 bps), consistent with the absence of pre-existing differential trends.

The *ExpSmoke* effect is economically significant. The 12.0 bps estimate represents 13.5% of one standard deviation of the healthcare offering yield spread and 12.9% of the credit spread between Aaa and Baa1 bonds, and corresponds to approximately $327 million in present value

interest costs on the $28.4 billion of healthcare municipal bonds issued in above-mean *ExpSmoke* counties. If expected exposure rises by another 72 $\mu g/m^3$ over the next decade based on current trends (1.07 standard deviations of *ExpSmoke*), repeat issues would incur roughly $1.19 billion more in present value interest costs.[5]

To put this magnitude in perspective, we compare our estimates to others in the literature on climate risk and the municipal bond market. For example, Goldsmith-Pinkham et al. (2023) find that a one standard deviation increase in sea level rise exposure raises municipal credit spreads by 5.3 bps, or about 9% of the average spread in their sample. Acharya et al. (2022) find that a one standard deviation increase in heat stress exposure raises municipal yield spreads by about 5 bps. Our estimate of 12.0 bps per standard deviation of *ExpSmoke* is more than twice as large in absolute terms. However, these studies benchmark their estimates against the average spread in the broad municipal market, which consists mostly of highly rated general obligation and school district bonds. Healthcare bonds are riskier, with a mean offering yield spread of 120.1 bps in our sample (Table 1), so a comparable credit shock produces a larger spread change for healthcare issuers. Relative to the average healthcare spread, our estimate amounts to 10% of the mean, close to the 9% reported by Goldsmith-Pinkham et al. (2023).

Internet Appendix A.2 shows that the $Health \times ExpSmoke$ estimate is robust to controlling for local wildfire activity and excluding county-years with wildfires or California (Table A.1), and to using tax- or call-adjusted yield spreads (Table A.2). In each case, the $Health \times InnovSmoke$ estimate is small and statistically insignificant. Consistent with the cash-flow mechanism in Section

[5]Using the duration approximation formula, $327 million $\approx 0.96 \times 0.0012 \times 10 \times \$28.4$ billion, where 10 years is the average duration of a healthcare issue and 0.96 is the size-weighted average *ExpSmoke* of healthcare issues in above-mean *ExpSmoke* counties. We also have that $1.19 billion $\approx 1.07 \times 0.0012 \times 10 \times \$92.6$ billion, where $92.6 billion is the total size of the 1,467 healthcare issues in Table 1. Scaling the structural estimates in Figure 6 of Goldsmith-Pinkham et al. (2023), the 12.0 bps effect corresponds to roughly a 4.5% to 13.4% decrease in hospital asset value, a 3.5% to 7.2% increase in asset volatility, or a combination of the two.

II, the effect is also concentrated in revenue bonds, which are repaid from hospital operating cash flows: a one standard deviation increase in *ExpSmoke* raises healthcare revenue bond spreads by 15.0 bps, compared with an insignificant 3.0 bps for healthcare general obligation issues, and the difference is statistically significant in a pooled regression ($p = 0.008$).

B. Underinsurance and Hospital Credit Risk

Our baseline findings indicate that expected smoke exposure increases borrowing costs for healthcare municipal bond issues. Our proposed mechanism for this finding is that the municipal bond market anticipates that smoke exposure 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, and Medicare-insured residents. For our purposes, the latter two categories are included in the underinsured definition because average ER 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 (4) 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 stan-

dard deviation increase in *ExpSmoke* is associated with a statistically significant 17.8 bps increase in healthcare borrowing costs in high-underinsurance counties, and a statistically insignificant 6.8 bps increase in healthcare borrowing costs in low-underinsurance counties, for a difference of 11.0 bps. The $Health \times InnovSmoke$ estimates are statistically insignificant in both subsamples (5.7 and -0.1 bps). In column (3), we retest the same regression model, except that we use our full sample of counties, and also interact $Health \times ExpSmoke$ and $Health \times InnovSmoke$ with $UndH$. (The associated lower-order terms are also included in this regression.) The point estimate on $Health \times ExpSmoke \times UndH$ is a statistically significant 7.2 bps, reflecting the evidence from the subsample regressions. The point estimate on $Health \times InnovSmoke \times UndH$ is smaller but also statistically significant (4.6 bps), suggesting that unexpected smoke is priced in counties where hospitals are most exposed to unprofitable demand. Overall, the evidence from these regressions is consistent with the expectation that smoke exposure 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 expansion of Medicaid under the Affordable Care Act (ACA) sharpens identification of the insurance channel. The ACA initially required states to extend Medicaid eligibility to households with incomes below 138% of the federal poverty line, with the federal government committing to pay 90% of the long-run cost. In June 2012, however, the Supreme Court ruled that states could not be required to expand, and states have since expanded at different times, based on decisions that were largely political rather than driven by local economic conditions (Gao, Lee and Murphy,

2022). Expansion moved many residents from the uninsured group into Medicaid, whose patients generate higher hospital margins than uninsured patients (Wilson and Cutler, 2014), and reduced hospitals' uncompensated care costs (Dranove, Garthwaite and Ody, 2016).

We first establish that expansion reduced uninsurance more in counties where it was initially high. We measure the county uninsured rate (*Unins*) as the percentage of residents under age 65 without health insurance using the Census Bureau's Small Area Health Insurance Estimates (SAHIE), and pre-expansion uninsurance (*PreUnins*) as the county average in 2008–2009 (before our bond sample begins). *MedExp* equals one after the state implements its expansion.[6] In a simple county-year panel regression with County and State $\times$ Year fixed effects and standard errors clustered by state, we find that expansion lowers the county uninsured rate by 0.32 percentage points for each percentage point of *PreUnins*, with a standard error of 0.02. Figure 3 shows that the decline in the uninsured rate begins at expansion and grows over the following two years.

We test the Medicaid expansion prediction within bonds in the secondary market, which allows us to follow the same healthcare bonds before and after their state expands. Intuitively, if insurance coverage is relevant for how smoke exposure affects healthcare credit risk, then the sensitivity of healthcare yields to *ExpSmoke* should decrease after Medicaid expansion, especially in counties with high pre-expansion uninsurance. We estimate the following model for secondary yield

[6]Implementation dates follow the Kaiser Family Foundation's tracker of state Medicaid expansion decisions. For example, Arizona implemented its expansion in 2014, Idaho and Nebraska implemented their expansions in 2020, and Wisconsin has not expanded. States that expanded after 2019 are treated as non-expansion states during our sample period.

spreads:

$$\begin{aligned} y_{bjt} &= \beta_E^M \cdot Health_b \times ExpSmoke_{jt} \times MedExp_{st} \times PreUnins_j \\ &+ \beta_I^M \cdot Health_b \times InnovSmoke_{jt} \times MedExp_{st} \times PreUnins_j \\ &+ \Gamma \cdot W_{bjt} + \delta \cdot Z_{jt} + \mu_b + \psi_{st} + \phi_{bt} + \lambda_{ht} + \varepsilon_{bjt}, \end{aligned} \tag{5}$$

where b represents the bond, W contains all of the lower-order terms from the two quadruple-interaction variables, and μ_b is a vector of bond fixed effects. The remaining variables are defined as before. β_E^M and β_I^M measure how the sensitivity of healthcare yields to *ExpSmoke* and *InnovSmoke* in high-uninsurance counties changes after the state expands Medicaid. Because expansion states may differ from non-expansion states in other ways that affect smoke sensitivity in high-uninsurance counties, we also report specifications that add $Health \times ExpSmoke \times ExpState \times PreUnins$, $Health \times ExpSmoke \times Post2014 \times PreUnins$, the corresponding *InnovSmoke* terms, and the lower-order interactions (*ExpState* indicates states that expanded by 2019, and *Post*2014 indicates observations on or after January 2014, when ACA coverage changes began nationwide). In these specifications, β_E^M and β_I^M are identified only from the change in the smoke sensitivity of healthcare bonds in high-uninsurance counties after their state expands Medicaid, relative to the change in non-expansion states over the same period.

Figure 4 first reports an event-study version of equation (5), in which the smoke terms are interacted with indicators for years relative to each state's expansion. Because the ACA originally required every state to expand Medicaid, a state's decision to expand, and hence its expansion date, was determined only after the June 2012 Supreme Court ruling that made expansion optional. We therefore measure event time from July 2012 onward and assign observations from expansion

states before the ruling to a separate pre-ruling category. The results in Panel A indicate that the *ExpSmoke* coefficients immediately before expansion are close to zero (0.4 and -0.5 bps) and statistically insignificant, while those after expansion are negative and significant at the 1% level in every year, ranging from -3.4 to -5.8 bps. Panel B reports the corresponding *InnovSmoke* coefficients, which show no clear pattern around expansion. Overall, these estimates show that the *ExpSmoke*-induced increase in healthcare yields in high-uninsurance counties is significantly attenuated after the state expands Medicaid.

Table 5 reports the estimates from equation (5), which are consistent with the evidence in Figure 4. Column (1) indicates that, following expansion, the *ExpSmoke*-yield effect decreases by 4.0 bps for each percentage point of pre-expansion uninsurance, thereby offsetting the positive pre-expansion effect. The estimates indicate that the effect of *InnovSmoke* is also attenuated following expansion (2.6 to 3.4 bps per percentage point of pre-expansion uninsurance), although Panel B of Figure 4 shows less evidence of a sharp change at expansion for *InnovSmoke* compared to *ExpSmoke*. In column (2), we include the $Health \times ExpSmoke \times ExpState \times PreUnins$ and $Health \times ExpSmoke \times Post2014 \times PreUnins$ controls, and find a slightly larger *ExpSmoke*-yield reduction (-5.4 bps). Columns (3) and (4) show similar results when we compare only states that expanded in January 2014 with states that had not expanded by 2019 (-4.5 and -5.9 bps). This comparison avoids the concern that the staggered estimates are biased by heterogeneous treatment effects across cohorts (Callaway and Sant'Anna, 2021; Sun and Abraham, 2021), as the comparison instead contains a single adoption cohort and uses only states that did not expand during the sample period as controls. Overall, these findings indicate that an increase in insurance coverage through state-level Medicaid expansion reduces the effect of expected smoke exposure on healthcare yields, and that the effect is concentrated in counties with high pre-expansion uninsurance,

where expansion reduced uninsurance the most. An implication of this finding is that limiting access to Medicaid or reducing Medicaid reimbursement rates could 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. We therefore separate wildfire smoke into its components attributable to in-state and out-of-state wildfires. Using 2010–2020 wildfire data processed by St. Denis et al. (2023) from the DHS National Incident Management System/Incident Command System (ICS), we estimate the following regression model:

$$Smoke_{jsy} = \beta \cdot F_{sy} \times \delta_s + \gamma \cdot F_{sy} + \delta_s + \varepsilon_{jsy}, \tag{6}$$

where F_{sy} consists of the number of wildfires, the number of structures damaged, and the log of burned acres in state s and year y.[7] F_{sy} is also interacted with state fixed effects δ_s to allow for geographic and meteorological differences between states. The predicted component is denoted $HomeSmoke$, and the residual, the part of *Smoke* not explained by in-state wildfire activity, is denoted *AwaySmoke*.[8]

We re-estimate equation (4) with the expected and innovation components of $HomeSmoke$ and

[7] To identify wildfire burn perimeters, we merge the ICS data with the US Forest Service Monitoring Trends in Burn Severity database (Eidenshink et al., 2007).

[8] We validate this interpretation of *AwaySmoke* by showing that it rises with wildfire activity in other states. In county-year regressions with state fixed effects, a one standard deviation increase in log burned acres in adjacent states raises *AwaySmoke* by 0.22 standard deviations ($t = 3.4$), and the estimate is unchanged when we add year fixed effects. *AwaySmoke* also rises with burned acres in non-adjacent states.

AwaySmoke, each standardized by its standard deviation. Because the wildfire data are annual, this section uses calendar-year exposure, with expectations based on the three preceding years. Column (1) of Table 6 indicates that a one standard deviation increase in expected $HomeSmoke$ raises healthcare borrowing costs by 15.1 bps, and a one standard deviation increase in expected *AwaySmoke* by 11.6 bps. The two are not statistically different from each other ($p = 0.36$). Innovations in $HomeSmoke$ are also priced (8.6 bps), whereas innovations in *AwaySmoke* are not (0.4 bps); this is consistent with a large in-state fire season being more informative about future exposure than an unusual year of drifting out-of-state smoke. Consistent with our earlier evidence supporting the insurance channel, we also find in column (2) that the effects of expected $HomeSmoke$ and *AwaySmoke* are 9.9 and 6.1 bps larger if $UndH$ is one standard deviation above its mean, while the innovation interactions are insignificant.

To illustrate the magnitudes, out-of-state smoke in Nevada was significantly above its mean during California's extreme 2020 fire season. Because only expected *AwaySmoke* is priced, such a year matters mainly through its effect on expected exposure. If repeated California fire seasons raised expected *AwaySmoke* in Nevada by one standard deviation, healthcare borrowing costs would rise by 11.6 bps, or about $732,000 in present value interest costs for a healthcare issue of average size ($63.1 million) with a ten-year duration.

Should we classify the expected *AwaySmoke* effect as a cross-state negative externality or spillover? If a state spends less on wildfire prevention and does not compensate healthcare providers in nearby states for the financial costs associated with drifting smoke plumes, then the "externality" classification is more appropriate. Internet Appendix A.3 and Table A.3 provide suggestive descriptive evidence that, relative to other Western states, California spends more on fire suppression and less on fire prevention per acre.

V. Hospital Outcomes

In this section, we test whether *Smoke* leads to adverse hospital-level outcomes that are internally consistent with the increase in hospital credit risk. First, we test whether *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

We first test whether smoke exposure increases ER visits (e.g., Aguilera et al., 2021; Heft-Neal et al., 2023). We use state-quarter emergency department discharge data from HCUP, which covers 35 states from 2010 to 2019 and records adult and pediatric ER visits by insurance group. We measure state-quarter population-weighted smoke $PM_{2.5}$ exposure, and split it into its expected (the average exposure in the same quarter of the three preceding years) and innovation components. We then regress the natural log of ER visits on standardized *ExpSmoke* and *InnovSmoke*. In this regression, we include state and year-quarter fixed effects and cluster the standard errors by state.

Panel A of Table 7 reports the results. A one standard deviation increase in expected quarterly smoke is associated with a 1.7% increase in ER visits. A one standard deviation increase in the quarterly smoke innovation is associated with a 0.6% increase in ER visits. Columns (2) and (3) indicate that expected smoke raises ER visits from underinsured and privately insured patients

by 1.7% and 1.3%, respectively. Column (4) indicates that the ratio of underinsured patients to privately insured patients is not affected by expected smoke or smoke innovations. Because underinsured patients account for about 75% of discharges, and the weighted-average margins for underinsured and privately insured patients are -25.8% and 39.6% (Wilson and Cutler, 2014), a smoke-driven increase in demand carries an average margin of roughly $0.75 \times (-25.8\%) + 0.25 \times 39.6\% \approx -9.5\%$, and an even lower average margin in high-underinsurance counties.[9]

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 into adverse real effects through the investment channel, especially if the hospital is already financially constrained (Stein, 2003; Adelino, Lewellen and Sundaram, 2015). A *Smoke*-induced reduction in future investment would therefore suggest that *Smoke* exacerbates financial constraints for hospitals.

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

[9] Panel B further shows that both expected smoke and smoke innovations also significantly increase pediatric asthma ER visits (10.2% and 3.1% per standard deviation), which is consistent with evidence in Noah et al. (2023) and Wilgus and Merchant (2024).

Formally, we test the following OLS regression model:

$$g(NFA)_{h,j,t+1} = \beta_E \cdot ExpSmoke_{j,t} + \beta_I \cdot InnovSmoke_{j,t} + \delta \cdot X_{h,j,t} + \gamma \cdot Z_{j,t} + \mu_h + \psi_{s,t} + \varepsilon_{h,j,t}, \quad (7)$$

where $ExpSmoke_{j,t}$ is the average calendar-year smoke exposure in county j over years $t-3$ to $t-1$, $InnovSmoke_{j,t}$ is year-t exposure minus $ExpSmoke_{j,t}$ (each standardized by its standard deviation), $g(NFA)_{h,j,t+1}$ is the one-year growth rate in net fixed assets for hospital h in county j and year t, $Z_{j,t}$ contains the county-level controls from equation (4), and μ_h and $\psi_{s,t}$ are hospital and State $\times$ Year 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).

Columns (1) and (2) of Table 9 report the results. Column (1) indicates that a one standard deviation increase in *ExpSmoke* reduces one-year net fixed asset growth by 2.4 percentage points (significant at the 5% level), while the effect of *InnovSmoke* is small and insignificant (-1.6 percentage points). Because the regressions include hospital fixed effects, the *ExpSmoke* coefficient is identified from changes in a county's expected exposure over our sample period. Like bond investors, hospitals therefore appear to respond to persistent smoke exposure rather than to year-to-year fluctuations. In column (2), we interact both components with $UndH$. The interactions are small and insignificant, and the *ExpSmoke* effect is unchanged. Because the hospital sample is much smaller than the bond sample, these tests have limited power to detect differences in the

investment response across levels of underinsurance. Overall, these results indicate that hospitals reduce investment in response to higher expected smoke exposure.

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 (7), 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 revenue based on revenue and expense data from HCRIS. We standardize this measure for ease of interpretation. As in the investment regressions, we include the county-level controls from our baseline regression.

Columns (3) and (4) of Table 9 report the results. Column (3) indicates that neither *ExpSmoke* nor *InnovSmoke* has a statistically significant effect on *Margin* for the average hospital. In column (4), we interact both components with $UndH$. In this case, we find that a one standard deviation increase in *ExpSmoke* (*InnovSmoke*) reduces *Margin* by 2.9% (3.2%) of one *Margin* standard deviation if $Underins/Hosp$ is one standard deviation above its mean. These results are consistent with our earlier intuition that smoke increases unprofitable demand from underinsured patients, especially in high-underinsurance counties.

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 expected smoke exposure is associated with significantly higher borrowing costs for healthcare service providers, whereas year-to-year deviations from expected exposure are largely not priced. 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. Furthermore, within-bond estimates show that the expansion of Medicaid insurance eligibility reduced the smoke sensitivity of healthcare yields where it lowered uninsurance the most, supporting a causal interpretation of the insurance channel. Expected 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 expected smoke lowers investment growth, and lowers profit margins in high-underinsurance counties, 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. Inter-

governmental 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. The EPA's "Good Neighbor Plan" of the Clean Air Act was meant to address a similar interstate problem for industrial pollution before being blocked by the Supreme Court in 2024 (AP News, 2024). 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, 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-ea23421c789992932673 39faf4453cdb`.

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.

Bernstein, Asaf, Matthew T Gustafson, and Ryan Lewis. 2019. "Disaster on the horizon: The price effect of sea level rise." *Journal of financial economics*, 134(2): 253–272.

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.

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, Brantly, and Pedro H. C. Sant'Anna. 2021. "Difference-in-Differences with Multiple Time Periods." *Journal of Econometrics*, 225(2): 200–230.

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

Cookson, J. A., E. Gallagher, and P. Mulder. 2026*a*. "Coverage neglect in homeowners insurance." Working paper. Pennsylvania State University.

Cookson, J. A., E. Gallagher, and P. Mulder. 2026*b*. "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, Kimberly, Xuelin Li, and Zihan Ye. 2026. "Hedging or Healing: How Business Cycle Exposure Affects the Safety Net." Working paper. Pennsylvania State University.

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.

Dranove, David, Craig Garthwaite, and Christopher Ody. 2016. "Uncompensated care decreased at hospitals in Medicaid expansion states but not at hospitals in nonexpansion states." *Health Affairs*, 35(8): 1471–1479.

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, Huasheng, Po-Hsuan Hsu, Kai Li, and Jin Zhang. 2020. "The Real Effect of Smoking Bans: Evidence from Corporate Innovation." *Journal of Financial and Quantitative Analysis*, 55(2): 387–427.

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

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.

Garnache, Cloé. 2026. "Does the Salience of Climate-Related Risk Affect Asset Prices?" *Journal of Financial and Quantitative Analysis*. Forthcoming.

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.

Garthwaite, Craig, Tal Gross, and Matthew J Notowidigdo. 2018. "Hospitals as insurers of last resort." *American Economic Journal: Applied Economics*, 10(1): 1–39.

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

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

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

Hsia, Renee Y, Arthur L Kellermann, and Yu-Chu Shen. 2011. "Factors Associated with Closures of Emergency Departments in the United States." *JAMA*, 305(19): 1978–1985.

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.

Kostovetsky, Leonard, Lin Peng, Christopher Rauh, and Muhammed Yönaç. 2026. "Measuring Local Climate Change Attention: Does It Affect Households and Firms?" *Journal of Financial and Quantitative Analysis*. Forthcoming.

Leland, Hayne E. 1994. "Corporate debt value, bond covenants, and optimal capital structure." *Journal of Finance*, 49(4): 1213–1252.

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.

Schwert, M. 2017. "Municipal bond liquidity and default risk." *The Journal of Finance*, 72: 1683–1722.

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.

Sun, Liyang, and Sarah Abraham. 2021. "Estimating Dynamic Treatment Effects in Event Studies with Heterogeneous Treatment Effects." *Journal of Econometrics*, 225(2): 175–199.

Tang, Ning, John Stein, Renee Y Hsia, Judith H Maselli, and Ralph Gonzales. 2010. "Trends and Characteristics of US Emergency Department Visits, 1997–2007." *JAMA*, 304(6): 664–670.

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.

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).

Kaiser Family Foundation (2026). "Status of State Action on the Medicaid Expansion Decision." https://www.kff.org/affordable-care-act/state-indicator/state-activity-around-expanding-medicaid-under-the-affordable-care-act/ (accessed October 18, 2026).

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 (2026). Small Area Health Insurance Estimates (SAHIE), 2008–2019. https://www.census.gov/data/datasets/time-series/demo/sahie/estimates-acs.html (accessed October 18, 2026).

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).

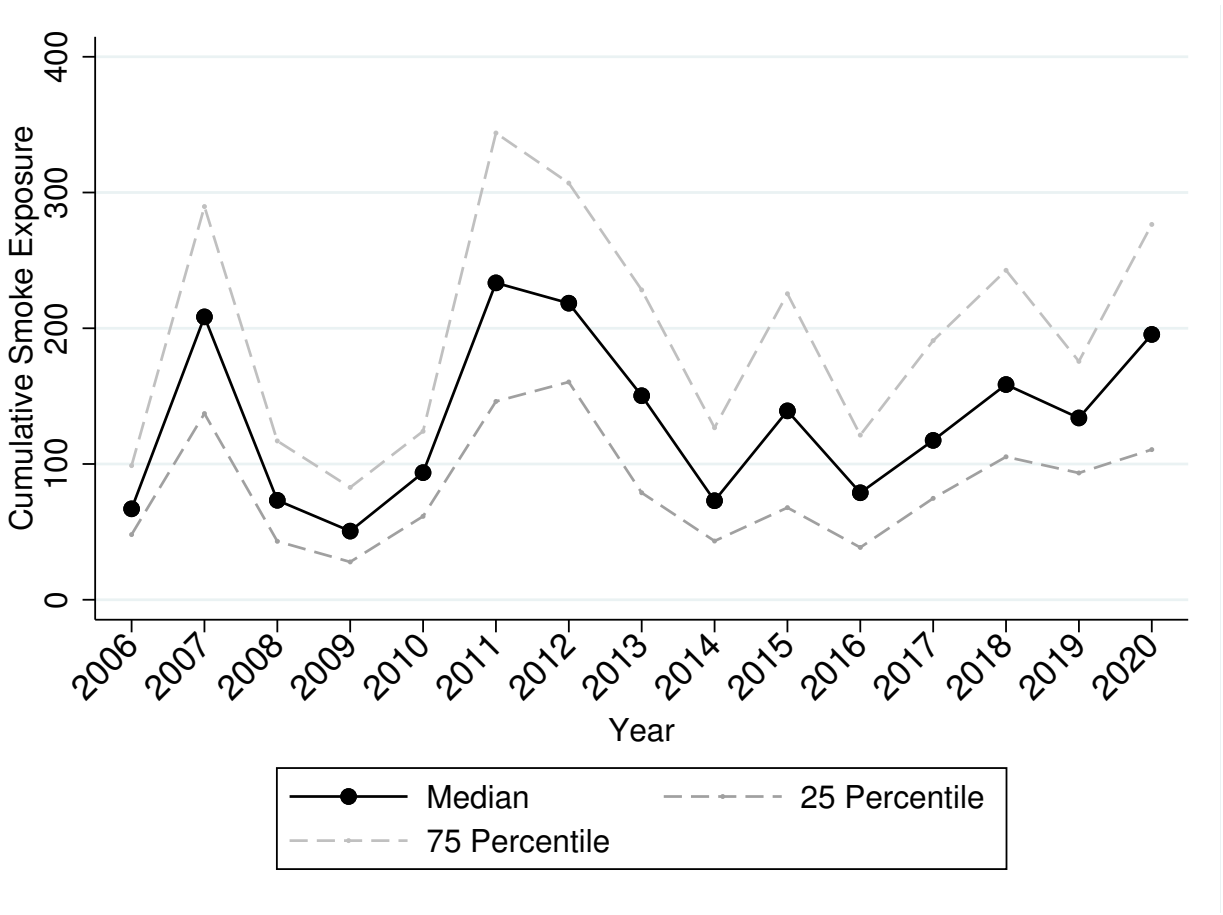
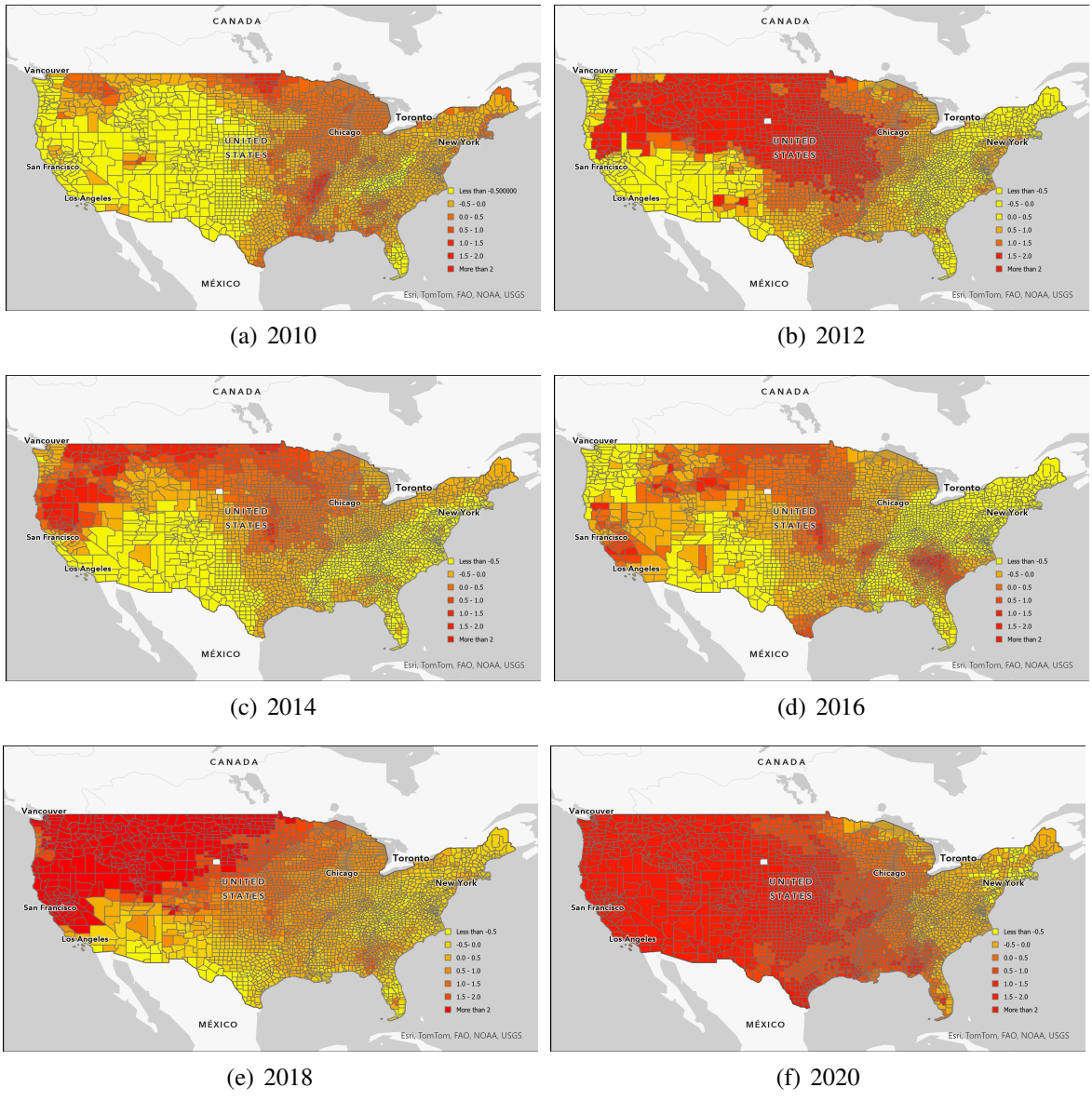


Figure 1. U.S. Wildfire Smoke by Year

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.



(a) 2010 (b) 2012

(c) 2014 (d) 2016

(e) 2018 (f) 2020

Figure 2. U.S. Wildfire Smoke Exposure

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

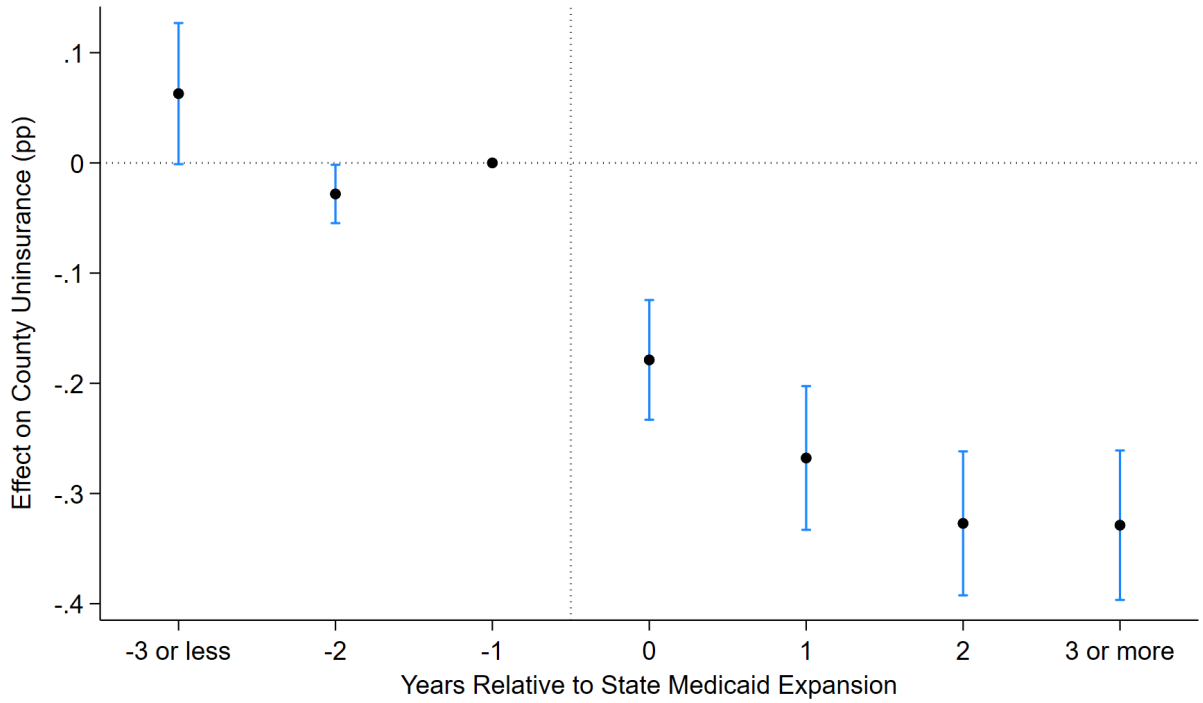


Figure 3. Medicaid Expansion and County Uninsurance

This figure reports the event study estimates γ_k from the county-year regression $Unins_{ct} = \sum_{k \neq -1} \gamma_k \cdot D_{st}^k \times PreUnins_c + \alpha_c + \psi_{st} + \varepsilon_{ct}$, where $Unins_{ct}$ is the percentage of residents under age 65 without health insurance in county c and year t, $PreUnins_c$ is the 2008–2009 county average of $Unins$, D_{st}^k indicates that year t is k years after state s implemented its Medicaid expansion under the ACA, and α_c and ψ_{st} are county and State $\times$ Year fixed effects. The first and last bins pool three or more years before and after expansion. The year before expansion ($k = -1$) is the omitted category, and states that did not expand by 2019 are the reference group. Each point estimate measures the change in the uninsured rate (in percentage points) per percentage point of $PreUnins$. The vertical bars are 95% confidence intervals based on standard errors clustered by state.

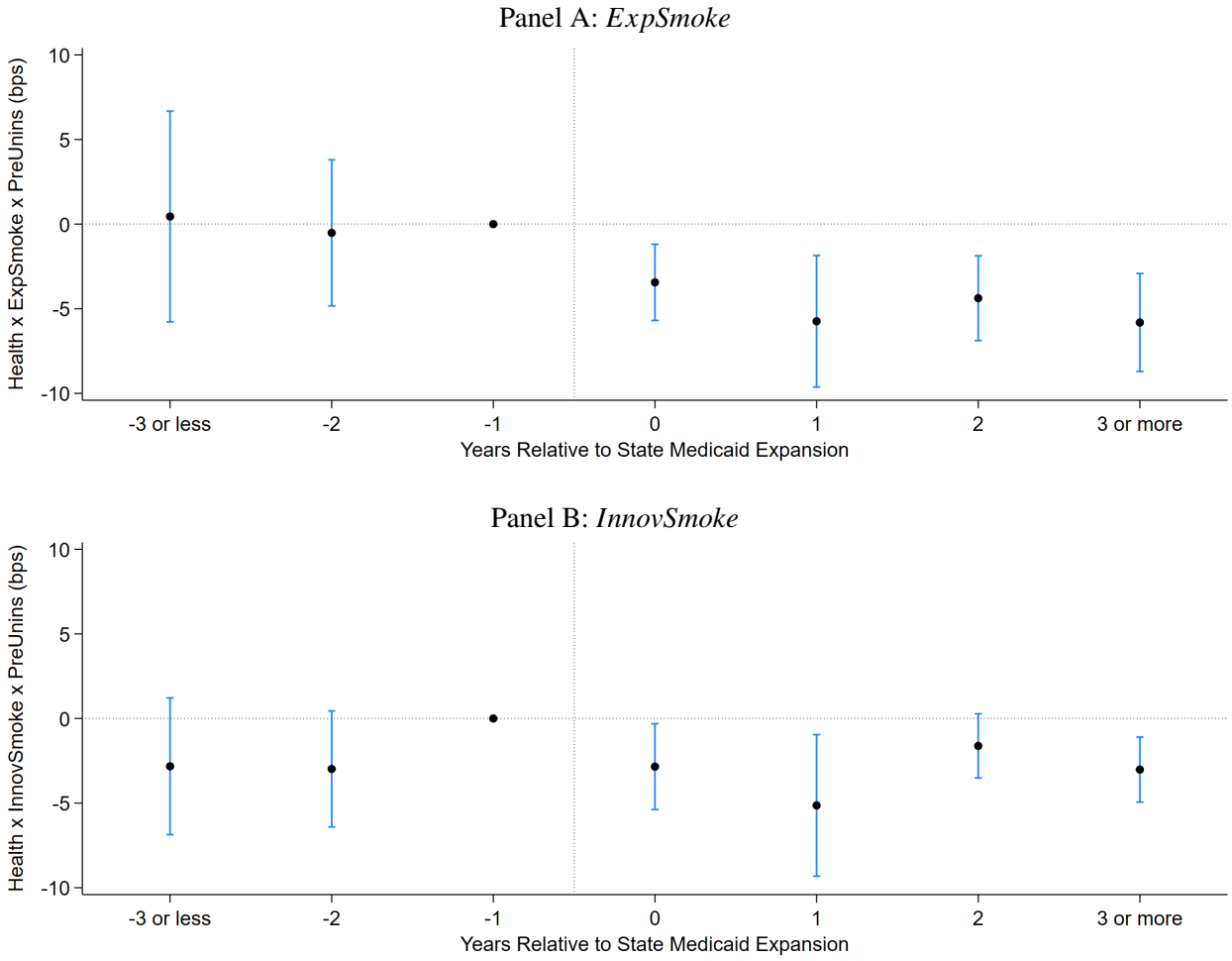


Figure 4. Medicaid Expansion and the Smoke Sensitivity of Healthcare Secondary Yields

This figure reports event study estimates of the coefficients on $Health \times ExpSmoke \times PreUnins$ (Panel A) and $Health \times InnovSmoke \times PreUnins$ (Panel B) by year relative to the state's Medicaid expansion. Both panels come from a single regression that follows column (1) of Table 5, except that $Health \times ExpSmoke \times PreUnins$, $Health \times InnovSmoke \times PreUnins$, and the lower-order terms are interacted with event-year indicators and a pre-ruling indicator. The first and last bins pool three or more years before and after expansion. The year before expansion and states that did not expand by 2019 form the reference group. The vertical bars are 95% confidence intervals based on standard errors clustered by county and year-month.

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 ($PM_{2.5}$ $\mu g/m^3$) 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. (%)
Health × *ExpSmoke*	0.122***	0.120***	0.232***	0.120***
	(0.030)	(0.029)	(0.050)	(0.045)
Health × *InnovSmoke*	0.020	0.020	0.074	0.024
	(0.034)	(0.033)	(0.069)	(0.023)
ExpSmoke	0.003	0.001		-0.008
	(0.011)	(0.011)		(0.013)
InnovSmoke	0.015**	0.016***		-0.015**
	(0.006)	(0.006)		(0.007)
lnSize	-0.036***	-0.035***	-0.046***	
	(0.007)	(0.007)	(0.010)	
Negotiated	0.099***	0.101***	0.107***	
	(0.015)	(0.014)	(0.023)	
GenObligation	-0.274***	-0.270***	-0.254***	
	(0.017)	(0.017)	(0.030)	
lnMaturity	0.170***	0.152***	0.149***	-0.153***
	(0.019)	(0.021)	(0.029)	(0.014)
County Controls	Yes	Yes	No	Yes
State-YM FE	Yes	Yes	No	Yes
Rating-YM FE	No	Yes	No	Yes
Insured-YM FE	No	Yes	Yes	Yes
Callable-YM FE	No	Yes	Yes	Yes
County FE	Yes	Yes	No	No
County-YM FE	No	No	Yes	No
Bond FE	No	No	No	Yes
Health-YM FE	Yes	Yes	Yes	Yes
Sample	OffMkt	OffMkt	OffMkt	SecMkt
Adj. R^2	0.506	0.517	0.522	0.807
N	67,693	67,447	40,370	7,762,949

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 *ExpSmoke*, *InnovSmoke*, and their interactions with *Health*. *Smoke* is the population-weighted cumulative amount of smoke $PM_{2.5}$ exposure in the county over the 12 months ending in the month of the yield observation. *ExpSmoke* is the average of *Smoke* over the three preceding 12-month windows; *InnovSmoke* is *Smoke* minus *ExpSmoke*. Both smoke measures are standardized. All columns use all non-healthcare bonds as the baseline group. Columns (1) to (3) use yield spread data from the offering market, and column (4) uses yield spread data from the secondary market. In column (4), 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. All specifications include *Health*× Year-Month fixed effects, which absorb the standalone *Health* indicator. 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) Yield Sp. (%)	(2) Yield Sp. (%)	(3) Yield Sp. (%)
$Health \times ExpSmoke$	0.178***	0.068	0.158***
	(0.052)	(0.050)	(0.030)
$Health \times InnovSmoke$	0.057	-0.001	0.050
	(0.046)	(0.053)	(0.035)
$ExpSmoke$	-0.010	0.003	0.000
	(0.015)	(0.017)	(0.011)
$InnovSmoke$	0.011	0.005	0.015***
	(0.008)	(0.009)	(0.005)
$Health \times ExpSmoke \times UndH$			0.072***
			(0.025)
$Health \times InnovSmoke \times UndH$			0.046**
			(0.020)
$ExpSmoke \times UndH$			0.003
			(0.004)
$InnovSmoke \times UndH$			0.001
			(0.003)
Controls	Yes	Yes	Yes
State-YM FE	Yes	Yes	Yes
Rating-YM FE	Yes	Yes	Yes
Insured-YM FE	Yes	Yes	Yes
Callable-YM FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Health-YM FE	Yes	Yes	Yes
Underins. Type	High	Low	All
Adj. R^2	0.520	0.516	0.518
N	37,124	29,166	67,382

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 *ExpSmoke* and *InnovSmoke* with $Health$ and $Underins/Hosp$ ($UndH$). *ExpSmoke* and *InnovSmoke* are defined as in Table 3. $UndH$ 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 $Health \times ExpSmoke$, $Health \times InnovSmoke$, and the lower-order terms. All columns use all non-healthcare bonds as the baseline group. The control variables are specified in the main text. All specifications include $Health \times$ Year-Month fixed effects, which absorb the standalone $Health$ indicator. 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: Medicaid Expansion and the Smoke Sensitivity of Healthcare Secondary Yields

	(1) Sec. Yield Sp.	(2) Sec. Yield Sp.	(3) Sec. Yield Sp.	(4) Sec. Yield Sp.
$H \times ExpSmoke \times MedExp \times PreUnins$	-0.040***	-0.054***	-0.045***	-0.059***
	(0.012)	(0.014)	(0.014)	(0.021)
$H \times InnovSmoke \times MedExp \times PreUnins$	-0.027***	-0.031**	-0.026***	-0.034*
	(0.008)	(0.013)	(0.009)	(0.020)
$H \times ExpSmoke \times PreUnins$	0.016**	0.002	0.016*	-0.003
	(0.007)	(0.011)	(0.008)	(0.011)
$H \times InnovSmoke \times PreUnins$	0.015***	0.012	0.016***	0.009
	(0.005)	(0.007)	(0.006)	(0.008)
$H \times ExpSmoke$	0.064	0.138	0.052	0.243*
	(0.054)	(0.112)	(0.057)	(0.127)
$H \times InnovSmoke$	-0.022	-0.018	-0.028	0.028
	(0.040)	(0.064)	(0.040)	(0.067)
$H \times ExpSmoke \times ExpState \times PreUnins$		0.007		0.003
		(0.016)		(0.019)
$H \times InnovSmoke \times ExpState \times PreUnins$		0.004		0.009
		(0.013)		(0.017)
$H \times ExpSmoke \times Post2014 \times PreUnins$		0.022**		0.027**
		(0.010)		(0.012)
$H \times InnovSmoke \times Post2014 \times PreUnins$		0.003		0.005
		(0.008)		(0.010)
Average $H \times ExpSmoke$ Effect	0.111**	0.125**	0.097**	0.131**
	(0.047)	(0.053)	(0.048)	(0.057)
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
Health-YM FE	Yes	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes	Yes
Sample	All	All	2014/Never	2014/Never
Adj. R^2	0.807	0.807	0.810	0.810
N	7,762,949	7,762,949	6,800,360	6,800,360

This table reports how Medicaid expansion changes the effects of *ExpSmoke* and *InnovSmoke* on healthcare secondary yield spreads (%). *PreUnins* is the 2008–2009 demeaned county uninsured rate under age 65; *MedExp* equals one after the state expands Medicaid; *ExpState* equals one for states that expanded by 2019; *Post*2014 equals one from January 2014 onward; and H denotes healthcare municipal bonds. Columns (2) and (4) add the analogous *ExpState* and *Post*2014 interactions. Columns (3) and (4) compare January 2014 expansion states with states that had not expanded by 2019. "Average $H \times ExpSmoke$ Effect" averages the full marginal effect of *ExpSmoke* over healthcare bond-months. Controls, weights, and sample follow column (4) of Table 3. Standard errors clustered by county and year-month are in parentheses; *, **, and *** denote significance at 10%, 5%, and 1%.

Table 6: In-State Smoke, Out-of-State Smoke, and Healthcare Borrowing Costs

	(1) Yield Sp. (%)	(2) Yield Sp. (%)
$Health \times ExpHomeSmoke$	0.151***	0.158***
	(0.044)	(0.047)
$Health \times InnovHomeSmoke$	0.086*	0.110**
	(0.044)	(0.050)
$Health \times ExpAwaySmoke$	0.116***	0.145***
	(0.034)	(0.038)
$Health \times InnovAwaySmoke$	0.004	0.043
	(0.040)	(0.041)
$Health \times ExpHomeSmoke \times UndH$		0.099*
		(0.053)
$Health \times InnovHomeSmoke \times UndH$		0.062
		(0.047)
$Health \times ExpAwaySmoke \times UndH$		0.061**
		(0.028)
$Health \times InnovAwaySmoke \times UndH$		0.023
		(0.031)
Controls	Yes	Yes
State-YM FE	Yes	Yes
Rating-YM FE	Yes	Yes
Insured-YM FE	Yes	Yes
Callable-YM FE	Yes	Yes
County FE	Yes	Yes
Health-YM FE	Yes	Yes
Adj. R^2	0.514	0.514
N	53,546	53,488

This table reports OLS estimates of the effects of in-state and out-of-state wildfire smoke on offering yield spreads (%). *HomeSmoke* is the predicted component of calendar-year *Smoke*, and *AwaySmoke* is the residual. *ExpHomeSmoke* (*ExpAwaySmoke*) is the average *HomeSmoke* (*AwaySmoke*) over the three preceding calendar years, and *InnovHomeSmoke* (*InnovAwaySmoke*) is *HomeSmoke* minus *ExpHomeSmoke* (*AwaySmoke* minus *ExpAwaySmoke*). Each of these four variables is standardized. Column (2) adds $UndH$ and its interactions with the four smoke components and their $Health$ interactions. All specifications include $Health\times$ Year-Month fixed effects. 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(ER)	(2) ln(ER_{und})	(3) ln(ER_{priv})	(4) ln(ER_{und}/ER_{priv})
ExpSmoke	0.017***	0.017***	0.013**	0.004
	(0.004)	(0.004)	(0.006)	(0.006)
InnovSmoke	0.006**	0.005	0.009***	-0.004
	(0.003)	(0.003)	(0.003)	(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(ER)	(2) ln(ER_{und})	(3) ln(ER_{priv})	(4) ln(ER_{und}/ER_{priv})
ExpSmoke	0.102***	0.100***	0.106***	-0.006
	(0.016)	(0.018)	(0.016)	(0.011)
InnovSmoke	0.031***	0.025**	0.041***	-0.015
	(0.007)	(0.010)	(0.007)	(0.011)
Ins. Type	Any	Underins.	Private	Any
State FE	Yes	Yes	Yes	Yes
Year-Qt. FE	Yes	Yes	Yes	Yes
Adj. R^2	0.987	0.981	0.974	0.768
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 population-weighted cumulative amount of smoke $PM_{2.5}$ exposure during the state-year-quarter. *ExpSmoke* is the average of smoke in the same quarter of the three preceding years, and *InnovSmoke* is *Smoke* minus *ExpSmoke*. Each variable is standardized. 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
$Margin$	0.039	0.039	-0.000	0.082	0.082
$g(NFA)_{t+1}$	0.037	-0.012	-0.057	0.061	0.233
$FinInv$	0.571	0.269	0.064	0.796	0.760
$g(SRev)$	0.037	0.033	-0.010	0.081	0.095
$OpInc$	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 revenue. $g(NFA)_{t+1}$ is the percentage change in hospital net fixed assets from year t to $t+1$. $FinInv$ 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 and Profit Margins

	(1) $g(NFA)_{t+1}$	(2) $g(NFA)_{t+1}$	(3) *Margin*	(4) *Margin*
ExpSmoke	-0.024**	-0.024**	0.013	0.016
	(0.012)	(0.012)	(0.028)	(0.028)
InnovSmoke	-0.016	-0.015	0.024	0.024
	(0.010)	(0.010)	(0.017)	(0.017)
ExpSmoke × *UndH*		0.004		-0.029*
		(0.008)		(0.017)
InnovSmoke × *UndH*		0.009		-0.032***
		(0.006)		(0.010)
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	0.094	0.095	0.714	0.714
N	9,241	9,241	9,320	9,320

This table reports OLS estimates of the effects of wildfire smoke pollution on hospital investment and profit margins. In columns (1) and (2), the dependent variable is the one-year percentage change in net fixed assets ($g(NFA)_{t+1}$), and in columns (3) and (4), the dependent variable is *Margin*, the standardized ratio of total hospital revenue minus total hospital expense to total hospital revenue. In columns (2) and (4), we interact *ExpSmoke* and *InnovSmoke* with $UndH$, the standardized log average number of underinsured residents per hospital in that county. *ExpSmoke* is the average population-weighted cumulative smoke $PM_{2.5}$ exposure in the county over the three preceding calendar years, and *InnovSmoke* is current-year exposure minus *ExpSmoke*; each is standardized by its own standard deviation. Hospital controls follow Adelino, Lewellen and Sundaram (2015): $g(SRev)$, the percentage change in net service revenue from $t-1$ to t; $OpInc$, operating income in year t divided by net fixed assets in $t-1$; $\log(TRev)$, the natural log of total revenue in year t; and $FinInv$, financial investments divided by net fixed assets in $t-1$. County controls are those in equation (4). 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

November 10, 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; telephone: (312) 355-8215) and Dermot Murphy (murphyd@uic.edu; telephone: (312) 355-4372) 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; telephone: (775) 682-7235) 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 the effects of wildfire smoke on physical health. Wildfire smoke contains a complex mixture of toxic fine particulate matter ($PM_{2.5}$), carbon monoxide, volatile organic compounds, and other toxic pollutants. $PM_{2.5}$ 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 $PM_{2.5}$ from other sources, and that an increase in wildfire-specific $PM_{2.5}$ 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 $PM_{2.5}$ 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. Clausing, 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 (4) 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 all four columns, the $Health \times ExpSmoke$ estimate is positive and statistically significant at the 1% level, and the $Health \times InnovSmoke$ estimate is small and statistically insignificant.

In Table A.2, we further show that our baseline results are unaffected when we use alternative constructions of the yield spread, and that the effect is concentrated in revenue bonds. 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 exempt from federal taxes, and also the

top marginal state income tax rate since interest on municipal debt is exempt from state taxes for in-state investors (excluding Illinois, Iowa, Oklahoma, and Wisconsin). 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 columns (3) and (4), we estimate the baseline model separately for revenue and general obligation issues. If smoke raises healthcare credit risk by reducing hospital operating cash flows, the effect should be concentrated in revenue bonds, which are repaid from those cash flows, rather than in general obligation bonds, which are backed by the tax base of the municipality. Consistent with this intuition, we find that a one standard deviation increase in *ExpSmoke* raises healthcare revenue bond spreads by 15.0 bps, compared with a statistically insignificant 3.0 bps for healthcare general obligation issues. In a pooled regression that interacts the smoke terms with a general obligation indicator, and that includes General Obligation $\times$ Year-Month and General Obligation $\times$ $Health$ fixed effects, we further find that the difference between the 15.0 bps healthcare revenue bond effect and the healthcare general obligation effect is statistically significant at the 1% level ($p = 0.008$).

Lastly, as a visual robustness test, we follow Borgschulte, Molitor and Zou (2022) and re-estimate the secondary market specification in column (4) of Table 3 in the main text, except that we replace *ExpSmoke* and *InnovSmoke* with current 12-month *Smoke* and its 12-month and 24-month leads and lags (that is, the 12-month exposure window shifted one and two years into the past or future). The lags allow us to examine how *Smoke* is incorporated into healthcare yields as market participants revise their expectations about smoke exposure. Meanwhile, the leads 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 A.1. The figure indicates that the contemporaneous *Smoke* effect on secondary healthcare bond yields is positive (2.1 bps) but not statistically significant, whereas the lagged effects are larger (5.1 bps for smoke one year earlier and 4.3 bps for smoke two years earlier). This pattern is consistent with the main text results, in that healthcare yields respond to accumulated past exposure, which shapes expectations about future exposure. Secondary healthcare yields also do not diverge significantly in response to lead *Smoke* shocks (1.4 bps and -1.9 bps), consistent with the absence of pre-existing differential trends.

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 than in 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 hazardous fuel reduction treatments 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. (%)
ExpSmoke	0.001	-0.001	0.010	-0.005
	(0.011)	(0.011)	(0.012)	(0.011)
$Health \times ExpSmoke$	0.120***	0.128***	0.129***	0.138***
	(0.029)	(0.030)	(0.033)	(0.033)
InnovSmoke	0.016***	0.005	0.012*	0.004
	(0.005)	(0.006)	(0.007)	(0.006)
$Health \times InnovSmoke$	0.020	0.023	0.010	0.015
	(0.033)	(0.035)	(0.036)	(0.037)
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
Health-YM FE	Yes	Yes	Yes	Yes
Model	Fire Control	Fire Excluded	CA Excluded	Fire/CA Excl.
Adj. R^2	0.517	0.514	0.511	0.512
N	67,447	64,190	62,981	61,093

We retest our baseline regression model in equation (4) 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). *ExpSmoke* and *InnovSmoke* are defined as in Table 3 and are each standardized by their own standard deviation. All specifications include $Health\times$ Year-Month fixed effects. Robust standard errors clustered by county and issuance year-month are reported in parentheses. The stars *, **, ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.2: Additional Robustness Tests for Baseline Regressions

	(1) y (Tax Adj.)	(2) y (Call Adj.)	(3) Yield Sp.	(4) Yield Sp.
ExpSmoke	0.014	0.008	-0.019	0.006
	(0.019)	(0.012)	(0.019)	(0.011)
$Health \times ExpSmoke$	0.234***	0.107***	0.150***	0.030
	(0.054)	(0.029)	(0.035)	(0.067)
InnovSmoke	0.036***	0.020***	0.017	-0.002
	(0.011)	(0.006)	(0.011)	(0.006)
$Health \times InnovSmoke$	0.068	0.014	0.083*	-0.096
	(0.065)	(0.036)	(0.046)	(0.074)
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
Health-YM FE	Yes	Yes	Yes	Yes
Model	Tax Adj.	Call Adj.	Revenue	Gen. Oblig.
Adj. R^2	0.632	0.490	0.492	0.578
N	66,744	67,447	21,247	44,247

We retest our baseline regression model in equation (4) of the main text (column (2) of Table 3) 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 the subsample of revenue bond issues; and in column (4), we use the subsample of general obligation issues. *ExpSmoke* and *InnovSmoke* are defined as in Table 3. All specifications include $Health\times$ Year-Month fixed effects. 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.

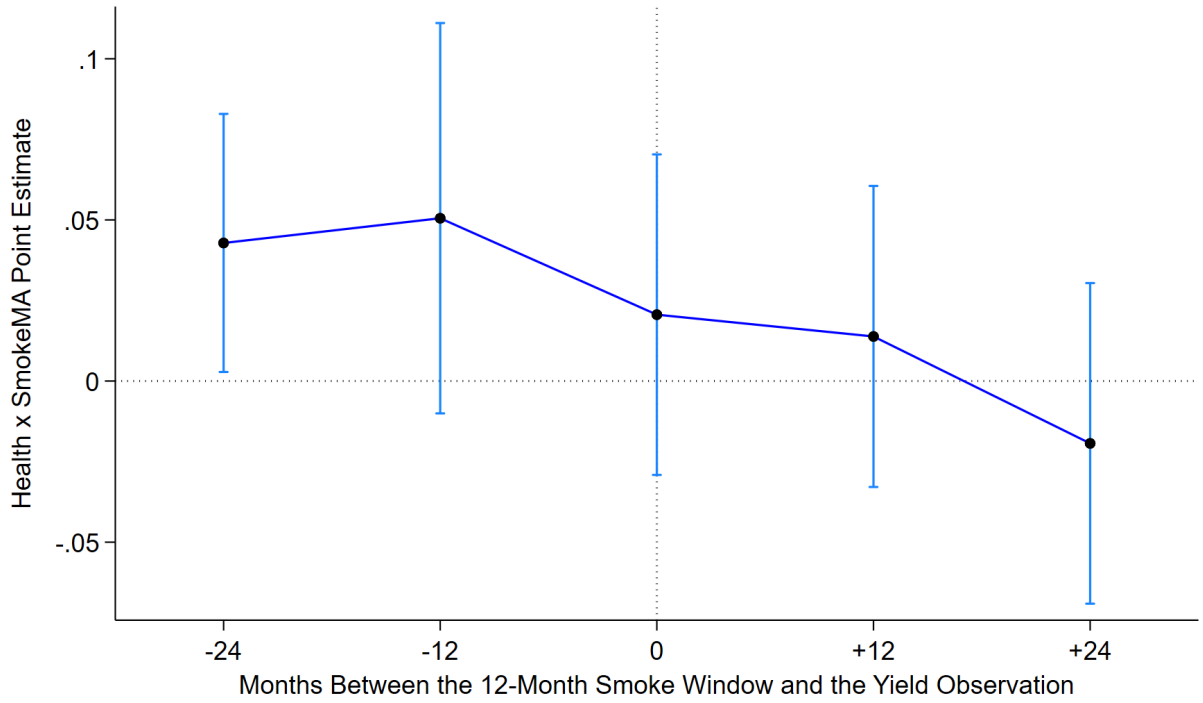


Figure A.1. Lag/Lead Effects of Smoke on Healthcare Secondary Yield Spreads

This figure reports the point estimates from a regression of secondary yield spread on $Health \times Smoke_m$, where $Smoke_m$ is the standardized 12-month smoke exposure window shifted by $m \in \{-24, -12, 0, +12, +24\}$ months relative to the month of the secondary yield spread observation; negative values correspond to smoke before the 12 months preceding the yield observation (lags), and positive values correspond to smoke in the future (leads). Methodologically, we test our baseline secondary yield spread model in column (4) of Table 3 in the main text, except that we also include the interactions of $Health$ with the 12-month and 24-month lags and leads of $Smoke$. The vertical bars are 95% confidence intervals for each $Health \times Smoke_m$ point estimate.

Table A.3: Fire Prevention and Suppression Expenditures

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

This table reports 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.

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`.

Childs, Marissa, Mariana Martins, Andrew Wilson, Minghao Qiu, Sam Heft-Neal, and Marshall Burke. 2025. "Growing Wildfire-Derived PM2.5 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.