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

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Abstract

Wildfire smoke pollution is associated with significantly higher healthcare municipal borrowing costs, amounting to $250 million in realized interest costs for high-smoke counties in 2010–2019, and an estimated $570 million over the following ten years. These costs are disproportionately higher in high-poverty or high-minority areas where there is more smoke-related uncompensated care. Out-of-state smoke is also associated with higher borrowing costs, suggesting poor wildfire management imposes externalities on nearby states. Our hospital-level analysis shows increases in asthma cases and unprofitable emergency room visits, tighter financial constraints, and reduced investment. Migration sorting exacerbates these effects by concentrating vulnerable households in high-smoke counties.

JEL Classification: R31, O18, N32

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I. Introduction

Drifting smoke plumes from wildfires and man-made fires impose major externalities on nearby areas. In India, for example, there are noticeable spikes in air pollution in urban areas during the fall months when rice farmers in rural areas burn crop residue. The Health Effects Institute estimates that 1.1 million Indian deaths in 2015 (10% of all Indian deaths in 2015) are attributable to air pollution each year and that 66,000 of those deaths are attributable to agricultural burning (IQAir, 2024). Meanwhile, in the United States, average temperatures have been steadily rising over time, and wildfire events are increasingly common. The Stanford Echo Lab estimates that drifting smoke plumes from U.S. wildfires have reversed long-term improvements in air quality in 35 states (Childs et al., 2022).

Smoke plumes are problematic because they increase the amount of fine particulate matter ($PM_{2.5}$) in the breathable air, which can be deadly to vulnerable populations (Deryugina et al., 2019). At high concentrations, $PM_{2.5}$ smoke pollution is associated not only with worse public health outcomes, but also worse negative economic outcomes such as reduced labor earnings (Isen, Rossin-Slater and Walker, 2017), weakened employment and labor force participation (Borgschulte, Molitor and Zou, 2022), decreased business activity (Addoum et al., 2023), and increased credit delinquencies (An, Gabriel and Tzur-Ilan, 2024). However, an understudied concern is that $PM_{2.5}$ smoke pollution also imposes major stress on healthcare providers, which are generally required to admit patients for respiratory emergencies while trying to maintain financial solvency.

This study aims to fill in this gap in the literature by examining the impact of wildfire $PM_{2.5}$ smoke pollution exposure on healthcare finance outcomes. The economics of the healthcare sector are unique because the increased demand for healthcare services can be profitable or unprofitable for the provider, depending on its operating capacity and patient demographics. For example, according to Wilson and Cutler (2014), hospital emergency room (ER) services are highly labor intensive and provide strong profit margins if the patient is privately insured (39.6%), but provide negative profit margins if the patient is Medicare-insured (−15.6%) or uninsured (−54.4%). Longer-term care facilities may also struggle to maintain strong profit margins when more residents suffer from smoke-related illnesses and have greater demand for healthcare services but only limited insurance coverage. Motivated by these competing effects, we conduct an in-depth analysis of how wildfire smoke ultimately affects healthcare providers' borrowing costs, real investment spending, and financial constraints.

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

We find that wildfire smoke pollution is associated with significantly higher healthcare municipal borrowing costs. A one standard deviation increase in wildfire smoke pollution is associated with a 6.4 basis point (bps) increase in the average offering yield spread for hospitals, and a 12.1 bps increase for nursing homes. For counties with above-mean wildfire smoke pollution, these effects correspond to additional interest expenses of $158 million for hospital bonds and $94 million for nursing home bonds issued during our sample period, for a total effect of about $250 million. Based on wildfire smoke trends, we predict an additional $570 million in interest expenses from repeat hospital and nursing home issues over the following ten years, raising the per-patient cost of care by $250 in the most smoke-affected counties.

In cross-sectional tests, we find that the borrowing cost effects are strongest in the American Northwest, where wildfire smoke is particularly intense. The effects are also 50% to 100% larger in high-poverty and high-minority counties, and for issuers that have weaker credit ratings and are closer to default. These findings suggest that wildfire smoke increases healthcare service demand that is unprofitable for healthcare providers, especially in areas with more vulnerable populations where environmental justice issues are salient (Banzhaf, Ma and Timmins, 2019).

Local investors form the backbone of the municipal bond market, and are typically considered the marginal investor because of tax advantages associated with holding local municipal bonds. Thus, their aggregate beliefs on climate change likely determine if wildfire smoke is priced in the healthcare municipal bond market. To test this channel, we obtain county-level data from the Yale Climate Opinions Maps website on the percentages of adults who are worried about global warming or believe that it will harm U.S. residents (Howe et al., 2015; Marlon et al., 2022). We find that the wildfire smoke effects on healthcare borrowing costs are especially strong in counties that believe global warming is worrisome or harmful, and no significant smoke effects in the remaining counties. These results suggest that wildfire smoke is priced in the healthcare municipal bond market as long as local investors believe that wildfires will remain a permanent part of the landscape due to climate change.

Wildfire smoke not only stays in the state of the fire but can drift for hundreds of miles to nearby states or even countries in some cases. Therefore, persistent wildfire smoke imposes major cost externalities on nearby states. In California, for example, frequent wildfires produce smoke plumes that significantly increase smoke pollution in Nevada. To understand the externality angle, we decompose wildfire smoke into its in-state and out-of-state components using wildfire data from the US Department of Homeland Security (DHS) Incident Command System (ICS). We find that out-of-state smoke effects on healthcare borrowing costs are almost as strong as the in-state effects, confirming that wildfire smoke is economically harmful to nearby states. To provide a sense of economic magnitude, over four million acres were burnt by local wildfires in California in 2020. Out-of-state smoke in Nevada increased by about 2.5 standard deviations as a result. Our estimates suggest that California wildfires in 2020 would have increased the total present value interest costs for an average \$90 million hospital issue in Nevada by \$1.6 million. These findings call for inter-state coordination and possibly federal intervention to tackle the growing economic and health issues surrounding wildfires, similar to how the "Good Neighbor" provision of the Clean Air Act was meant to regulate inter-state industrial pollution prior to being blocked by the Supreme Court in 2024 (AP News, 2024*b*).

Our proposed mechanism is that wildfire smoke pollution increases healthcare service demand that is unprofitable for the service provider, thereby increasing their credit risk and associated borrowing costs. Using the HCRIS database, we test the validity of this mechanism by examining the effect of wildfire smoke on hospital investment spending and investment sensitivity to endowment cash flow shocks. Standard Q-theory suggests that the latter variable is a useful proxy for financial constraint in the non-profit hospital setting (Adelino, Lewellen and Sundaram, 2015). Adapting the methodology in Adelino, Lewellen and Sundaram (2015), we find that a one standard deviation increase in wildfire smoke is associated with a 2.3% reduction in investment spending and a 45% increase in investment-cash flow sensitivity over two-year investment horizons. These results suggest that hospitals respond to smoke-related financial stress by reducing their long-term capital expenditures and increasing their reliance on stock market returns to generate investment capital.

We further test the validity of our proposed mechanism using data on real health outcomes and hospital admissions patterns from the Centers for Disease Control and Prevention (CDC) and the Kaiser Family Foundation (KFF), a non-profit organization for health policy research. First, we confirm that wildfire smoke pollution can be associated with a significant increase in asthma cases. Second, we show that wildfire smoke pollution is also associated with a significant increase in emergency room (ER) visits, presumably due to the increase in respiratory illnesses implied by our first test. The increase in smoke-related ER visits is likely to be a source of significant financial stress for hospitals because ER profit margins for treating vulnerable populations are highly negative (Wilson and Cutler, 2014).[1]

Lastly, we test the effect of wildfire smoke on long-term migration patterns. Intuitively, if persistent wildfire smoke causes younger residents to leave the county, then the resulting patient composition skews toward Medicare-insured residents who are less likely to change their address (US Census Bureau, 2024). First, using population data from the US Census Bureau American Community Survey (ACS), we find that counties with persistently high smoke exposure are associated with a significant decrease in population aged under 65 years, but no change in population aged 65 years or older. Second, using household data from the Federal Reserve Bank of New York (FRBNY) Equifax Consumer Credit Panel (CCP), a nationally representative sample of Equifax credit report data, we find that individuals below the age of 40 with an Equifax Risk Score above 780 are more likely to move out of

[1]These results are also consistent with findings from the health economics literature. For instance, extant research has shown that wildfire smoke pollution is associated with increased Medicare hospital admissions for respiratory illnesses (Liu et al., 2017), negative mental health outcomes (Molitor, Mullins and White, 2023), and increased mortality and respiratory hospitalizations (Gould et al., 2024).

high-smoke counties in the long-run. Overall, these results suggest that persistent wildfire smoke skews the composition of patients toward residents who are older or have weaker credit scores, further contributing to lower profit margins and increased credit risk.

Our study contributes to three major strands of literature. First, we build on the literature on climate finance. Painter (2020) shows that investors demand higher yields on long-term municipal bonds from counties exposed to high sea level rise (SLR) risk, as rising sea levels can cause significant damage to local infrastructure. Using a sample of school municipal bonds, which are highly dependent on local property taxes, Goldsmith-Pinkham et al. (2023) show that the SLR risk premium is attributable to property tax uncertainty, as SLR risk redirects investment away from exposed areas. Acharya et al. (2022) show that local exposure to damage from heat stress is associated with higher municipal bond yield spreads.[2] Other studies similarly focus on the perceived risk of physical damage to property (e.g., Baldauf, Garlappi and Yannelis, 2020; Bakkensen and Barrage, 2022; Auh et al., 2022; Jerch, Kahn and Lin, 2023; Butler and Uzmanoglu, 2023; Bakkensen, Phan and Wong, 2024). To our knowledge, we are the first to document that climate-induced wildfire smoke imposes costly externalities on the healthcare municipal bond market, which has important implications for the efficiency of public health provision.

Second, our study speaks to the debate on regulation and financial costs. Earlier studies document significant cost savings in the healthcare market due to the 2010 Affordable Care Act (Finkelstein, Hendren and Luttmer, 2019; Duggan, Gupta and Jackson, 2022; Gao, Lee and Murphy, 2022), and we show a reversal of these savings in high-smoke counties. Burke et al. (2021) show that wildfire smoke is eroding the success of the Clean Air Act in reducing

[2] Jeon, Barrage and Walsh (2024) explore the effect of wildfire risk on school district bond spreads and find that municipalities facing higher future wildfire risk increases are already having to pay higher borrowing costs today.

air pollution, making it difficult for municipalities to meet the US EPA's National Ambient Air Quality Standards (NAAQS). For NAAQS-incompliant counties, local municipal borrowing costs are higher because they are required by the EPA to make major changes to their investment policies (e.g., limiting new industrial development) to get pollution under control, increasing regulatory uncertainty (Jha, Karolyi and Muller, 2020). Hence, our findings imply that besides having a direct impact on healthcare municipal finance, drifting wildfire smoke could also trigger inter-state externalities in the form of increased regulatory costs.

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

II. Data

A. Municipal Bonds

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

We supplement the Mergent database with data from Bloomberg on the US county associated with each issue. The US county information is crucial for our analysis because it allows us to merge the municipal issue data with county-level wildfire smoke pollution data. We also supplement the Mergent database with county demographic data from the US Census Bureau's American Community Survey. Lastly, following other municipal bond

[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.

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

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

B. Wildfire Smoke Pollution

We obtain smoke pollution data at the daily census tract level from the Stanford Echo Lab. The data feature the predicted level of surface $PM_{2.5}$ concentrations from wildfire smoke plumes. Childs et al. (2022) construct the smoke pollution measure using a machine learning algorithm that detects anomalous variations in $PM_{2.5}$ concentrations on days when smoke is likely in the air. Their approach combines ground monitor $PM_{2.5}$ readings from EPA monitoring stations with satellite imagery from the National Oceanic and Atmospheric Administration (NOAA) Hazard Mapping System (HMS) and air trajectories from known fires from the NOAA Air Resources Laboratory. For each ten-kilometer grid and day, they calibrate the smoke $PM_{2.5}$ predictions using: (1) distance to the closest fire clusters, (2) mean eastward wind speeds, (3) mean westward wind speeds, (4) mean air and dewpoint temperatures at two meters from the ground, (5) total precipitation, (6) sea-level and surface pressure, (7) planetary boundaries, and (8) land use and elevation. As a result, the predicted smoke $PM_{2.5}$ measure excludes all the variation from non-wildfire factors such as industrial pollution, road density, dust, and elemental carbon (Childs et al., 2022).

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

Table II provides the mean and standard deviation for each pollution metric by year, and Figure 1 plots the quartile cutoffs for each pollution metric by year. We observe oscillations in wildfire smoke pollution with an upward trend. Figures 2 and 3 illustrate the geographic variation in annual cumulative smoke exposure and smoke days over time. To get a sense of relative changes over time, the former variable is standardized by subtracting its mean from 2006–2009 and then dividing the difference by its standard deviation from 2006–2009. The figures indicate that wildfire smoke pollution was concentrated in the Midwest during the early part of the decade, but has since shifted to the Northwestern US, with an exposure intensity spilling over to many states in other regions.

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

III. Smoke Pollution and Healthcare Borrowing Costs

The purpose of this section is to test the effect of wildfire smoke pollution on healthcare municipal borrowing costs. The main dependent variable in this section is y_{ijt}, the offering yield spread for municipal issue i in county j and year-month t. The main independent variable is $Smoke_{jt}$, the annual population-weighted cumulative $PM_{2.5}$ exposure across census tracts within each county j for each year t. For ease of interpretation for our regression tests, we also normalize this variable by subtracting its mean (145.5 $\mu g/m^3$) and then dividing the difference by its standard deviation (108.9 $\mu g/m^3$). In the next two subsections, we present results from our baseline analysis and cross-sectional analyses by county demographic and issue characteristics, and in the third subsection, we test for differences by whether the local population holds strong beliefs or worries about climate change. In the fourth subsection, we analyze borrowing cost externalities from wildfire smoke by decomposing our smoke measure into its in-state and out-of-state components.

A. *Baseline Analysis*

We begin by testing the effects of smoke pollution on the borrowing costs of hospital and nursing home municipal issues relative to other issues in each county. Formally, we test the following baseline OLS regression model:

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

where $Hospital$ and $Nurse$ are indicator variables that equal one if the municipal bond issue is used to finance a hospital project and a nursing home project, respectively. The β^C coefficient measures the effect of *Smoke* on non-healthcare yield spreads, and the β^H and β^N coefficients measure the effects of *Smoke* on hospital and nursing home yield spreads, respectively, relative to non-healthcare yield spreads. The issue-level control variable vector X consists of the standalone $Hospital$ and $Nurse$ indicator variables, the natural logs of issue size and size-weighted number of years until maturity, indicator variables for whether the bond is callable, insured, general obligation, and issued in the negotiated market, and indicator variables for each credit rating and the unrated category.[4] The county-level control variable vector Z consists of the natural logs of median household income and median gross rent, the Hispanic and Black population shares, the housing vacancy rate, and the renter-to-owner occupancy ratio. The vector ϕ_{ijy} consists of state-year fixed effects and county fixed effects. Standard errors are clustered by county and year-month of issuance.

The results of this regression test are reported in Table III, column (1). We find that

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

a one standard deviation increase in *Smoke* is associated with a 6.4 basis point increase in the offering yield spread for hospitals, a 12.1 basis point increase for nursing homes, and no change for non-healthcare issues. In column (2), we use industrial development bonds as our baseline instead of all non-healthcare bonds and find slightly stronger results (7.8 basis points for hospitals and 13.3 bps for nursing homes). Unlike healthcare bonds, industrial development bonds should be unaffected by fluctuations in public health expenditures or events that strain the daily operation of hospitals and nursing homes. In columns (3) and (4), we use an alternative smoke measure (*SmokeDays*), calculated as the number of days in the year when wildfire smoke covered at least 75% of the census tracts in the county. (This variable is also normalized by subtracting its mean of 38.9 days and then dividing the difference by its standard deviation of 22.4 days.) For these tests, we find statistically significant point estimates that are similar to those in the first two columns.

The borrowing cost effects are highly economically significant. For hospitals, the 6.4 basis point effect represents 10.7% of one standard deviation in the offering yield spread (59.9 basis points), 6.9% of the credit spread between Aaa and Baa1 bonds (92.8 basis points), and \$158 million in additional present value interest costs on the \$24.7 billion worth of hospital municipal bonds issued in above-mean *Smoke* counties. For these counties, the additional costs reverse the interest rate savings from the US Affordable Care Act documented in Gao, Lee and Murphy (2022). For nursing homes, the 12.1 basis point effect represents 20.2% of one standard deviation in the offering yield spread, 10.7% of the credit spread between Aaa and Baa1 bonds, and \$94.4 million in additional present value interest costs on the \$6 billion worth of nursing home municipal bonds issued in above-mean *Smoke* counties.[5]

[5]The present value interest costs are calculated using the duration approximation formula. For hospital issues with an average duration of 10 years, the 0.064% yield spread effect corresponds to a $0.064\% \times 10 = 0.64\%$ reduction in bond value, or $0.64\% \times \$24.7$ billion = \$158 million in present value interest costs. Similar calculations are applied for nursing home issues with an average duration of 13 years.

Looking forward, if average annual exposure to wildfire smoke $PM_{2.5}$ were to increase again by 72 $\mu g/m^3$ over the next decade (or about 20 additional smoke days per year), then our baseline results suggest that repeat issues of hospital and nursing home municipal bonds from our 2010–2019 sample would amount to another \$570 million in out-of-sample present value interest expenses.[6] We also estimate the per-patient total interest cost associated with wildfire smoke for future healthcare issues, where the *Smoke* shock is based on the decennial change in average $PM_{2.5}$ wildfire smoke exposure from Figure 4.[7]

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

B. *Cross-Sectional Tests*

Our proposed mechanism is that wildfire smoke increases the public health expenditures, thereby stressing financial positions and increasing credit risks in the healthcare sector. For low-income counties, these effects may be more pronounced because the healthcare provider

[6]To determine the total present-value interest costs, we use the duration approximation formula for the \$94 billion in hospital issues, the \$18 billion in nursing home issues, the *Smoke* point estimates from Table III, column (1), the average durations of approximately 10 years for hospitals and 13 years for nursing homes, and a 72 $\mu g/m^3$ *Smoke* effect normalized by its standard deviation.

[7]For each county, we again use the duration approximation formula using the total healthcare issue size in 2010–2019 and the average duration to obtain the total future interest cost. The per-patient cost is the total future interest cost divided by 10% of county population size, where 10% is approximately the average number of patient admissions per capita (Kaiser Family Foundation, 2022).

admits more uninsured patients who cannot afford to pay the associated bills and insured patients who cannot afford to pay the associated deductibles. In this section, we test the validity of this mechanism by exploiting cross-sectional variation in income levels and related demographic characteristics.

We retest the baseline regression model in equation (1) using a stratified sampling approach based on poverty rate or minority share. First, we divide US counties into "high poverty" and "low poverty" subsamples using the median poverty rate of 16.7%.[8] The subsample regression results are reported in columns (1) and (2) of Table IV. We find that the *Smoke* effect on hospital yields is about 50% larger in high-poverty counties (7.8 basis points) compared to low-poverty counties (5.2 basis points), and that the *Smoke* effect on nursing home yields is about twice as large in high-poverty counties (19.9 basis points versus 9.9 basis points). In columns (3) and (4), we divide US counties into "high minority" or "low minority" using the median combined share of Black and Hispanic residents (16.7%), and similarly find that the *Smoke* effects are larger in the high minority counties. Overall, our results suggest that wildfire smoke pollution not only directly affects vulnerable populations, but also indirectly affects these populations by placing greater financial stress on lower-income hospitals and nursing homes.

A stratified sampling approach based on credit quality is also useful for identifying how wildfire smoke affects healthcare credit risk, as lower-quality issuers may have less capacity to handle patients with smoke-related illnesses. We divide our sample of issues into three groups: high quality (the top two credit rating categories), medium quality (the next two categories), and low quality (the remaining categories or unrated). Table V reports the

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

subsample regression results. We find the most substantial *Smoke* effects for low-quality hospitals (10.7 basis points) and nursing homes (22.4 basis points), a marginally statistically significant *Smoke* effect of 8.3 basis points for medium-quality hospitals, and no effect for medium-quality nursing homes. For high-quality hospitals, we find a statistically significant *Smoke* effect of -15.7 basis points, suggesting an improvement in credit quality. One possible reason is that these hospitals are better able to adapt to climate change — like investing in sustainable clean indoor air — than low-quality hospitals, which triggers a "flight-to-quality" among consumers that value clean air (Kahn and Zhao, 2018).

C. Climate Change Beliefs and Perceptions

Local investors form the backbone of the municipal bond market, and are typically considered the marginal investor because of tax advantages associated with holding local municipal bonds (Babina et al., 2021; Garrett et al., 2023). Thus, their beliefs about climate change likely determine if wildfire smoke is priced in the healthcare municipal bond market. In this section, we test if beliefs about the long-term effects of climate change influence our *Smoke* point estimates.

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

We re-test the baseline regression model in equation (1) using these four survey-based subsamples. Table VI, column (1) indicates that a one standard deviation increase in *Smoke* in "high worry" counties is associated with a highly significant 6.9 bps increase in average offering yield spread for hospitals, and a 13.2 bps increase for nursing homes. For the "low worry" subsample in column (2), however, we find no statistically significant *Smoke* effects for hospitals or nursing homes. The results in columns (3) and (4) are similar, with highly significant *Smoke* point estimates in "high harm" counties, and no statistically significant point estimates in "low harm" counties. Overall, these results suggest that wildfire smoke is priced by local investors in the municipal bond market as long as they believe that climate change and the associated wildfires will persist in the long run. Conversely, in "low worry" and "low harm" counties, local investors are more likely to believe that wildfire smoke is caused by one-off wildfires, and thus not a public health or economic concern in the long run.[9]

D. The Effects of Smoke from Out-of-State Wildfires

Lastly, we analyze the borrowing cost effects associated with in-state versus out-of-state wildfire smoke pollution. In California, for example, regularly occurring wildfires cause pollution in neighboring states that may be associated with significant economic costs. From

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

an identification perspective, an analysis of out-of-state wildfire smoke is useful for our purposes because it is uncorrelated with economic effects attributable to in-state wildfire damages. From a policy perspective, an analysis of borrowing cost externalities associated with out-of-state wildfire smoke is also useful for guiding neighboring states or the federal government on how these states can share the ex-post costs associated with wildfire smoke or the ex-ante costs associated with wildfire prevention.

We decompose our *Smoke* variable into its in-state and out-of-state components using the 2010–2020 data on wildfires processed by St. Denis et al. (2023) and compiled by the US Department of Homeland Security National Incident Management System/Incident Command System (ICS). Specifically, we model the *Smoke* process as follows:

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

where $F_{j,s,y}$ is a vector of in-state wildfire variables that includes the number of wildfires, the number of structures damaged, and the natural log of the number of wildfires burnt acres in county j, state s, and year y.[10] To account for variation in state-level smoke predictability due to geographic factors such as weather, we interact the F_{jsy} vector with state fixed effects (δ_s), and also include the standalone F_{jsy} and δ_s variables in the regression. The predicted component of wildfire smoke is attributable to in-state smoke ($HomeSmoke$), and the residual component is attributable to out-of-state smoke ($AwaySmoke$). For ease of interpretation, both variables are normalized by subtracting their respective means and then dividing the resulting differences by their respective standard deviations.

We re-test the baseline regression model in equation (1), except that we replace the

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

Smoke variable with its in-state and out-of-state components. The results are reported in column (1) of Table VII. We find that *HomeSmoke* and *AwaySmoke* significantly increase borrowing costs for hospitals and nursing homes. In particular, a one standard deviation shock to *HomeSmoke* and *AwaySmoke* increases hospital borrowing costs by 5.6 basis points and 7.1 basis points, respectively, and increases nursing home borrowing costs by 11.7 basis points and 9.5 basis points, respectively. Within each sector, the point estimate on *HomeSmoke* is also not statistically different from the point estimate on *AwaySmoke*, suggesting that costly externalities associated with wildfire smoke are independent of where the smoke originates. Lastly, in column (2), we re-test the same regression model as column (1), except that we use only industrial development bonds as our baseline instead of all non-healthcare bonds. In this case, we find slightly stronger results, but the takeaway remains the same, in that in-state and out-of-state wildfire smoke affects healthcare yields about equally.

To better understand the economic implications of out-of-state wildfire smoke, consider an example involving California and Nevada. In 2020, California experienced one of the most extreme wildfire years on record, with over four million acres burned by local wildfires. In the same year, out-of-state smoke in neighboring Nevada was about 2.5 standard deviations higher than its mean. Our point estimates in Table VII indicate that hospital borrowing costs would have increased by $7.1 \times 2.5 = 17.8$ basis points as a result of the out-of-state smoke, while nursing home borrowing costs would have increased by $9.5 \times 2.5 = 23.8$ basis points. For a hospital issue with an average size of \$90 million and duration of ten years, the out-of-state smoke effect would increase total present value interest costs by \$1.6 million. Similarly, for a nursing home issue with an average size of \$30 million and duration of 13 years, the out-of-state smoke effect would increase total present value interest costs by about

$0.9 million. Therefore, if Nevada were scheduled to build a hospital and nursing home in a high out-of-state smoke year such as 2020, then wildfire smoke from California would increase costs by $2.5 million.

To be sure, we are not necessarily suggesting that California should transfer $2.5 million to Nevada every time Nevada wants to borrow money to build a hospital and nursing home in a high-smoke year. Wildfires are notoriously difficult to prevent or suppress, especially given that many factors, such as rising global temperatures, are outside of a state's control. Nonetheless, US governments spend over $3 billion per year to suppress wildfires, with some success. For factors within a state's control, good faith efforts to prevent wildfires and adaptively invest in wildfire-resilient technologies should be recognized by neighboring states and the federal government when considering these cost externalities (Baylis and Boomhower, 2022). The Environmental Protection Agency (EPA) could also coordinate efforts between neighboring states to prevent wildfires, with partial guidance from our cost estimates. However, a recent Supreme Court decision to block the EPA's "Good Neighbor" provision of the Clean Air Act, which was meant to reduce inter-state pollution externalities, could potentially complicate these coordination efforts.

IV. Mechanism Tests

Our baseline results indicate that wildfire smoke pollution significantly increases healthcare credit risk. Our proposed mechanism is that persistent wildfire smoke strains healthcare financial resources and increases the likelihood of uncompensated care, thereby weakening healthcare financial positions. In the next three subsections, we test the validity of this mechanism by analyzing the real effects of wildfire smoke pollution on (1) hospital investment spending, (2) health outcomes and hospital admissions patterns, and (3) intercounty residential sorting, which can detrimentally change the patient mix for hospitals.

A. *Real Investment Spending*

Q-theory predicts that investment spending should not respond to cash flow shocks in a frictionless market. In the presence of frictions, there are two common reasons that investment spending responds to cash flow shocks: agency conflicts and financial constraints (Stein, 2003). In the non-profit hospital setting, Adelino, Lewellen and Sundaram (2015) provides strong evidence that investment sensitivity to cash flow shocks is attributable only to the latter, likely due to the unique governance structure of non-profit hospitals. We use hospital financial variables from the Healthcare Cost Report Information System (HCRIS) database (maintained by the Centers for Medicare & Medicaid Services using required annual cost reports from hospitals) to test the effects of wildfire smoke pollution on non-profit hospital investment spending and financial constraints.

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

Formally, we test the following OLS regression model:

$$\begin{aligned} g(NFA)_{h,i,t+k} &= \beta_1 \cdot Smoke_{i,t} + \beta_2 \cdot InvInc_{h,i,t} + \beta_3 \cdot InvInc_{h,i,t} \times Smoke_{i,t} \\ &+ \delta \cdot X_{h,i,t} + \varepsilon_{h,i,t}, \end{aligned} \tag{3}$$

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

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

B. Real Health Effects

Our proposed mechanism is that wildfire smoke affects healthcare credit risk and investment due to greater unprofitable healthcare service demand, especially in high-poverty areas where hospitals provide more uncompensated care (Miller, 2012). In the previous sections, we provided evidence of harmful financial effects from wildfire smoke. In this subsection, we explore the real effects by examining how wildfire smoke affects the frequency of asthma cases and hospital admissions patterns.

B.1. Asthma Cases

Our first step is to test if wildfire smoke increases the likelihood of respiratory illness. We obtain data from the Centers for Disease Control and Prevention (CDC) and the 2020

Behavioral Risk Factor Surveillance System (BRFSS) on the number of asthma cases. The information on asthma cases is taken from state statistics on the burden of asthma among adults for those who answered "yes" to the questions: "Have you ever been told by a doctor or other health professional that you had asthma?" and "Do you still have asthma?"

We regress the number of asthma cases on our *Smoke* variable and also include the country control variable vector Z from our baseline regression and state and year fixed effects. The results in Table X indicate that adults are more likely to receive an asthma diagnosis during years with high levels of wildfire smoke pollution, which is consistent with findings in Noah et al. (2023) and Wilgus and Merchant (2024). In particular, column (1) indicates that a one standard deviation increase in *Smoke* is associated with approximately 9,000 additional asthma cases, which would amount to an additional cost of up to \$2.25 million for municipal hospitals in the state if the per patient cost attributable to smoke pollution is approximately \$250. When we replace the state fixed effects with county fixed effects in column (2), the effect is slightly larger, with a point estimate of approximately 10,000 additional asthma cases. Lastly, in column (3), we replace *Smoke* with $HomeSmoke$ and $AwaySmoke$, and we find that both measures are associated with a significant increase in asthma cases. Therefore, out-of-state wildfire smoke also imposes significant health externalities on nearby states, in addition to the borrowing cost externalities highlighted earlier.

B.2. Hospital Admissions and ER Visits

The increase in respiratory problems is likely associated with an increase in costly ER visits to hospitals. To explore this idea, we collect annual data on total emergency room visits and hospital admissions from the Kaiser Family Foundation (KFF), a non-profit organization for health policy research, and the American Hospital Association. We regress the number of ER visits (in thousands) on *Smoke*, and also include the county-level control variable vector Z and state and year fixed effects. The results in Table XI, column (1) indicate that a one standard deviation increase in *Smoke* is associated with approximately 2,500 additional ER visits. In column (2), we retest the same regression, except that we replace *Smoke* with *HomeSmoke* and *AwaySmoke*. In this case, we find that both measures are associated with significantly more ER visits, indicating that out-of-state smoke also imposes real health externalities on neighboring states. Lastly, we repeat the tests in columns (1) and (2), except that we use hospital admissions per 1,000 people as the dependent variable. The results in columns (3) and (4) indicate that hospital admissions similarly increase in response to greater in-state or out-of-state wildfire smoke levels.

C. Migration and Residential Sorting

Another channel that could exacerbate the proposed mechanism at the intensive margin is the impact of smoke pollution on residential sorting. In a Rosen-Roback framework, which models the intercity equilibrium between wages and housing costs, increased exposure to smoke pollution acts as a negative amenity shock that motivates out-migration of high-skilled labor with relaxed mobility constraints (Rosen, 1979; Roback, 1982; Glaeser and Gyourko, 2005).[11] By contrast, smoke pollution is less likely to motivate the out-migration of low-skilled labor because the associated individuals tend to be older or low-income, and thus have tighter mobility constraints (US Census Bureau, 2024). The resulting patient mix could be highly unprofitable for healthcare service providers since older residents are more likely to be Medicare-insured and low-income residents are more likely to be uninsured,

[11] In a related study, Lopez and Tzur-Ilan (2023) provide evidence that households view air quality as a public amenity and consider access to clean air when deciding where to live. Similarly, Chen, Oliva and Zhang (2022) find that air pollution is responsible for out-migration in China.

thereby generating worse profit margins for hospital ER departments (Wilson and Cutler, 2014). In this section, we examine the long-run impact of smoke pollution exposure on the county population stock and county population flow.

C.1. Population Stock

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

$$\%PopChange_{js} = \beta \cdot SmokeChange_{js} + \delta_s + \varepsilon_{js}, \tag{4}$$

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

The results are reported in column (1) of Table XII. We find that a one standard deviation increase in $SmokeChange$ is associated with a 0.68% decline in county-level population from 2009 to 2019, which is statistically significant at the 10% level. This supports the hypothesis that worsening air quality is associated with greater out-migration. However, this migration behavior is not uniform across all age groups. Column (2) shows that a one standard deviation increase in $SmokeChange$ is associated with a statistically significant

0.78% decrease in residents under 65 years of age, and column (3) shows that there is no statistically significant effect for residents aged 65 or older.[12] These results suggest that the patient mix for hospitals skews more toward older residents in high-smoke areas and away from younger residents who would otherwise subsidize costly healthcare for older residents, further contributing to higher financial stress and credit risk for healthcare providers.

C.2. Population Flow

Skilled labor is correlated with not only age but also other individual characteristics such as credit score. In the next step of our analysis, we use the FRBNY Equifax Consumer Credit Panel (CCP) data set to explore the effect of smoke pollution on residential sorting and county population flow in the cross-section of age and credit score. The CCP data set is a nationally representative sample of Equifax credit report data that contains a random, anonymous sample of 5% of US consumers with a credit file. The panel data allow us to observe if somebody has migrated from a particular county over an extended period.

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

$$OutMigration_{ij} = \beta \cdot SmokeChange_{js} + \gamma \cdot X_i + \delta_s + \varepsilon_{js}. \tag{5}$$

In this specification, $OutMigration_i$ is an indicator variable that equals 1 if individual i moves out of county j by 2019, X_i is a vector of individual characteristics that includes

[12]Methodologically, for these last two tests, we decompose the *%PopChange* into two additive components: the change in population under 65 years of age as a percentage of county population in 2009, and the change in population at least 65 years of age as a percentage of county population in 2009, where 65 is the qualifying age for Medicare.

age and Equifax Risk Score (a measure of credit score by Equifax) in 2010, and δ_s is a vector of state fixed effects. We test this regression model for subsamples of individuals based on different combinations of age and Equifax Risk Score. In terms of age, we focus on individuals aged 20-40 (1.8 million observations), 40-65 (4.5 million observations), and 65-85 (2.5 million observations). In terms of Equifax Risk Score, we focus on individuals with an Equifax Risk Score below 620 (subprime borrowers; 1.8 million observations), between 620-660 (near-prime borrowers; 0.7 million observations), 660-720 (prime borrowers; 1.2 million observations), 720-780 (super-prime borrowers; 1.7 million observations), above 780 (super-prime borrowers; 3.4 million observations). Altogether, we test 15 subsample regressions based on these three age groups and five Equifax Risk Score groups.

The resulting point estimates on $SmokeChange$ for these subsample regressions are reported numerically in Table XIII and graphically in Figure 6. We find that the strongest smoke effect on out-migration is concentrated among individuals aged 20-40 that are in the highest Equifax Risk Score group (greater than 780). For these individuals, a one standard deviation increase in $SmokeChange$ is associated with a statistically significant 2.2% increase in out-migration. Statistically significant effects are also observed for individuals aged 40-65 that are in the highest or second-highest Equifax Risk Score groups (1.1% and 1.0%, respectively). Overall, these results indicate that wildfire smoke is more likely to drive away younger, productive residents with strong credit scores, thereby skewing the patient composition toward the remaining age and credit score groups. Given that many older residents are Medicare-insured and many low-credit residents are uninsured, hospitals in high-smoke areas are likely exposed to greater operational challenges and credit risks in the long run.

V. Conclusion

Climate change and global warming are fueling wildfires that produce drifting smoke plumes with hazardous pollutants. Cities that are downwind of wildfires do not suffer from physical damage but harbor the health and economic costs of poor air quality, even when the origin of the fire is in another state or country. The incidences of wildfire smoke pollution events will become even worse in the future. According to a 2024 report by First Street, the number of poor air quality days in some areas of California is expected to increase from 60 days to over 90 days in the next 30 years.

We estimate the financial costs of wildfire smoke by leveraging variation in a novel measure of wildfire smoke exposure that is exogenous to the local economy. We show that exposure to wildfire smoke is associated with significantly higher borrowing costs for hospitals and nursing homes. Specifically, a one standard deviation increase in smoke pollution exposure is associated with a 6.4 bps increase in offering yield spread for hospital issues, and a 12.1 bps increase for nursing home issues. In high-smoke counties, these effects translate to about \$158 million in realized interest costs for hospital issues and \$94 million in realized interest costs for nursing home issues. Importantly, we also find that out-of-state wildfire smoke is associated with significantly higher borrowing costs, suggesting that poor wildfire management imposes costly externalities on other states due to traveling smoke plumes. Given that climate change is projected to increase the frequency of wildfires, these interest costs are expected to continue increasing not only in the Western US, but also in eastward states such as Texas and Minnesota, and even as far as Georgia and Florida.

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

The costs associated with preventing and suppressing wildfires are increasingly large due to climate change, and intergovernmental cooperation is crucial for addressing wildfire events. Our evidence suggests that policymakers should account for the costly externalities that wildfires impose on other states when determining how to optimally split the associated prevention and suppression costs. A key question policymakers should be asking is who is best suited to determine how much to spend on wildfire mitigation, especially in light of these externalities. For within-state smoke, if adjacent local governments are unable to negotiate on how to split the associated costs, then the state government may be able to step in and determine an optimal solution. For smoke that travels across state borders, the federal government and the EPA may be more effective in coordinating efforts to suppress wildfires 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.* National Bureau of Economic Research Cambridge, MA, USA.

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

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

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

AP News. 2022. "Regulators try to stop unlawful nursing home debt collection." Retrieved at: `https://apnews.com/article/health-nursing-homes-government-and-politics-cd4fa9b5b61c4fa83a6338449651531c`.

AP News. 2024*a*. "New California rule aims to limit health care cost increases to 3% annually." Retrieved at: `https://apnews.com/article/california-health-care-costs-target-cap-0aefad8c177ed3e0447dc4e17258be08`.

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

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

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

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

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

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

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

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

Baylis, Patrick W, and Judson Boomhower. 2022. "Mandated vs. voluntary adaptation to natural disasters: The case of US wildfires." Working paper. National Bureau of Economic Research.

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

Betermier, Sebastien, Sara B Holland, and Sean Wilkoff. 2024. "How Do Retiree Health Benefit Promises Affect Municipal Financing?" *Available at SSRN 4602990.*

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.

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

Butler, Alexander W, and Cihan Uzmanoglu. 2023. "A Market-based Measure of Climate Risk for Cities." *Available at SSRN 4603875.*

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.

Chen, Shuai, Paulina Oliva, and Peng Zhang. 2022. "The effect of air pollution on migration: Evidence from China." *Journal of Development Economics*, 156: 102833.

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.

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

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

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

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.

Duggan, Mark, Atul Gupta, and Emilie Jackson. 2022. "The impact of the Affordable Care Act: Evidence from California's hospital sector." *American Economic Journal: Economic Policy*, 14(1): 111–151.

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.

Finkelstein, Amy, Nathaniel Hendren, and Erzo FP Luttmer. 2019. "The value of medicaid: Interpreting results from the oregon health insurance experiment." *Journal of Political Economy*, 127(6): 2836–2874.

Gao, Pengjie, Chang Lee, and Dermot Murphy. 2020. "Financing dies in darkness? The impact of newspaper closures on public finance." *Journal of Financial Economics*, 135(2): 445–467.

Gao, Pengjie, Chang Lee, and Dermot Murphy. 2022. "Good for your fiscal health? The effect of the Affordable Care Act on healthcare borrowing costs." *Journal of Financial Economics*, 145(2): 464–488.

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

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

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

Gould, Carlos F, Sam Heft-Neal, Mary Johnson, Juan Aguilera, Marshall Burke, and Kari Nadeau. 2024. "Health effects of wildfire smoke exposure." *Annual Review of Medicine*, 75(1): 277–292.

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.

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

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

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

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

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

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

Kahn, Matthew E, and Daxuan Zhao. 2018. "The impact of climate change skepticism on adaptation in a market economy." *Research in Economics*, 72(2): 251–262.

Kaiser Family Foundation. 2022. "Hospital admissions per 1,000 population by ownership type." Retrieved at: `https://www.kff.org/other/state-indicator/admissions-by-ownership/`.

Liu, Jia Coco, Ander Wilson, Loretta J Mickley, Francesca Dominici, Keita Ebisu, Yun Wang, Melissa P Sulprizio, Roger D Peng, Xu Yue, Ji-Young Son, et al. 2017. "Wildfire-specific fine particulate matter and risk of hospital admissions in urban and rural counties." *Epidemiology (Cambridge, Mass.)*, 28(1): 77.

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.

Lopez, Luis A, and Nitzan Tzur-Ilan. 2023. "Air pollution and rent prices: Evidence from wildfire smoke." *Available at SSRN 4537395*.

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

Miller, Sarah. 2012. "The effect of insurance on emergency room visits: an analysis of the 2006 Massachusetts health reform." *Journal of Public Economics*, 96(11-12): 893–908.

Molitor, David, Jamie T Mullins, and Corey White. 2023. "Air pollution and suicide in rural and urban America: Evidence from wildfire smoke." *Proceedings of the National Academy of Sciences*, 120(38): e2221621120.

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.

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

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

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.

US Census Bureau. 2024. "Domestic migration of older Americans: 2015-2019." Retrieved at: `https://www.census.gov/library/publications/2022/demo/p23-218.html`.

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

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

DATA REFERENCES

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Table I: Municipal Bond Summary Statistics by Sector

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

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

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

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

Table II: Wildfire Smoke Pollution Summary Statistics

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

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

Table III: The Effect of Smoke Pollution on Municipal Bond Offering Yield Spread (%)

	(1) Yield Spread (%)	(2) Yield Spread (%)	(3) Yield Spread (%)	(4) Yield Spread (%)
$Smoke \times Hospital$	0.064***	0.078***		
	(0.021)	(0.018)		
$Smoke \times Nurse$	0.121***	0.133***		
	(0.040)	(0.034)		
$Smoke$	0.008	0.000		
	(0.006)	(0.008)		
$SmokeDays \times Hospital$			0.060***	0.091***
			(0.021)	(0.022)
$SmokeDays \times Nurse$			0.077**	0.113***
			(0.033)	(0.034)
$SmokeDays$			0.018*	0.013
			(0.010)	(0.015)
Controls	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Rating-Year FE	Yes	Yes	Yes	Yes
Insured-Year FE	Yes	Yes	Yes	Yes
Callable-Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Baseline	Non-HN	Ind. Dev.	Non-HN	Ind. Dev.
Adj. R^2	0.581	0.646	0.581	0.646
N	76,863	28,596	76,863	28,596

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

Table IV: Smoke Pollution Effects by County Demographics

	(1) Yield Spread (%)	(2) Yield Spread (%)	(3) Yield Spread (%)	(4) Yield Spread (%)
$Smoke \times Hospital$	0.078***	0.052*	0.065***	0.039
	(0.025)	(0.031)	(0.023)	(0.032)
$Smoke \times Nurse$	0.199**	0.099*	0.252***	0.124**
	(0.086)	(0.050)	(0.069)	(0.059)
$Smoke$	-0.003	0.006	0.010	0.002
	(0.009)	(0.005)	(0.008)	(0.008)
Controls	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Rating-Year FE	Yes	Yes	Yes	Yes
Insured-Year FE	Yes	Yes	Yes	Yes
Callable-Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Subsample	High Poverty	Low Poverty	High Minority	Low Minority
Adj. R^2	0.567	0.579	0.613	0.557
N	34,235	42,138	41,356	35,430

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

Table V: Smoke Pollution Effects by Bond Quality

	(1) Yield Spread (%)	(2) Yield Spread (%)	(3) Yield Spread (%)
$Smoke \times Hospital$	-0.157*	0.083*	0.107***
	(0.085)	(0.043)	(0.022)
$Smoke \times Nurse$	-0.096	0.000	0.224***
	(0.092)	(0.089)	(0.044)
$Smoke$	-0.001	0.001	0.018*
	(0.009)	(0.006)	(0.010)
Controls	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes
Rating-Year FE	Yes	Yes	Yes
Insured-Year FE	Yes	Yes	Yes
Callable-Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Rating Subsample	High	Medium	Low/Unrated
Adj. R^2	0.398	0.497	0.632
N	15,427	25,807	34,777

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

Table VI: Smoke Pollution Effects by Climate Change Beliefs

	(1) Yield Spread (%)	(2) Yield Spread (%)	(3) Yield Spread (%)	(4) Yield Spread (%)
Smoke × *Hospital*	0.069***	0.044	0.073***	0.036
	(0.019)	(0.048)	(0.019)	(0.050)
Smoke × *Nurse*	0.132***	0.016	0.123**	0.056
	(0.047)	(0.087)	(0.051)	(0.071)
Smoke	0.006	-0.004	0.006	0.013
	(0.006)	(0.010)	(0.006)	(0.012)
Controls	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Rating-Year FE	Yes	Yes	Yes	Yes
Insured-Year FE	Yes	Yes	Yes	Yes
Callable-Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Subsample	High Worry	Low Worry	High Harm	Low Harm
Adj. R^2	0.602	0.513	0.604	0.513
N	61,017	15,802	59,374	17,444

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

Table VII: In-State and Out-of-State Smoke Effects on Offering Yield Spread

	(1) Yield Spread (%)	(2) Yield Spread (%)
$HomeSmoke \times Hospital$	0.056**	0.086***
	(0.026)	(0.022)
$HomeSmoke \times Nurse$	0.117**	0.144***
	(0.047)	(0.047)
$AwaySmoke \times Hospital$	0.071***	0.063***
	(0.020)	(0.020)
$AwaySmoke \times Nurse$	0.095**	0.096**
	(0.047)	(0.043)
$AwaySmoke$	0.005	-0.002
	(0.005)	(0.010)
Controls	Yes	Yes
State-Year FE	Yes	Yes
Rating-Year FE	Yes	Yes
Insured-Year FE	Yes	Yes
Callable-Year FE	Yes	Yes
County FE	Yes	Yes
Baseline	Non-HN	Ind. Dev.
Adj. R^2	0.585	0.654
N	60,348	21,390

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

Table VIII: Hospital Financial Summary Statistics

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

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

Table IX: The Effects of Smoke Pollution on Hospital Investment

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

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

Table X: The Effects of Smoke Pollution on Asthma Cases

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

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

Table XI: The Effects of Smoke Pollution on Hospital Utilization

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

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

Table XII: The Effects of Smoke Pollution on Municipal Population

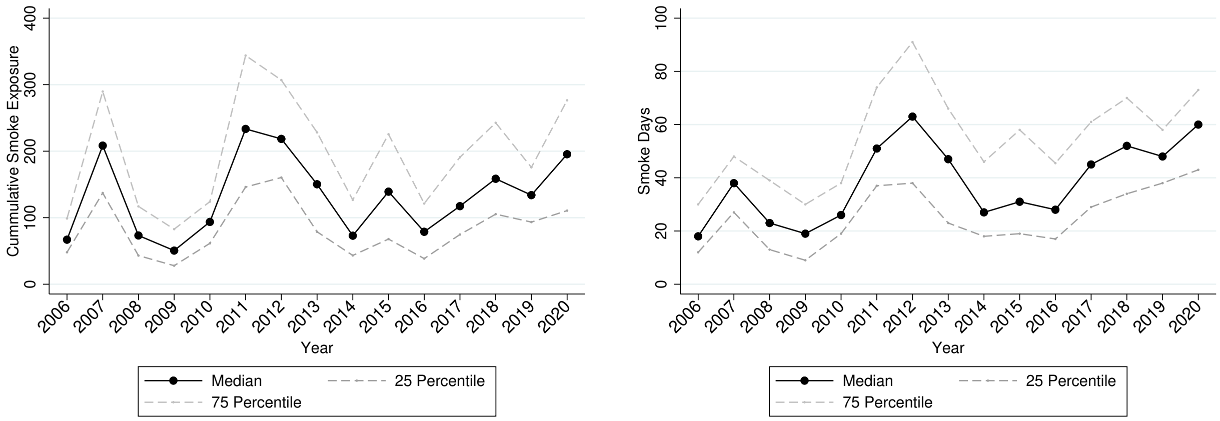
	(1) $\%PopChange$	(2) $\%PopChange < 65$	(3) $\%PopChange \geq 65$
$SmokeChange$	-0.684*	-0.775**	0.091
	(0.390)	(0.382)	(0.168)
State FE	Yes	Yes	Yes
Adj. R^2	0.140	0.121	0.177
N	3,106	3,106	3,106

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

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

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

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

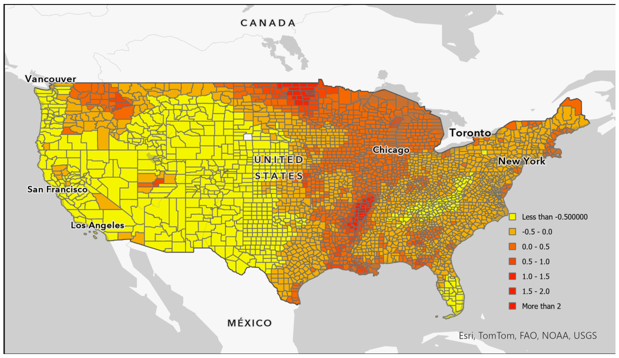


(a) Smoke Exposure

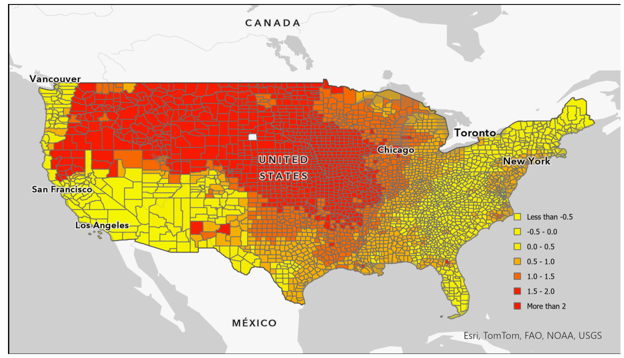
(b) Smoke Days

Figure 1. U.S. Wildfire Smoke by Year

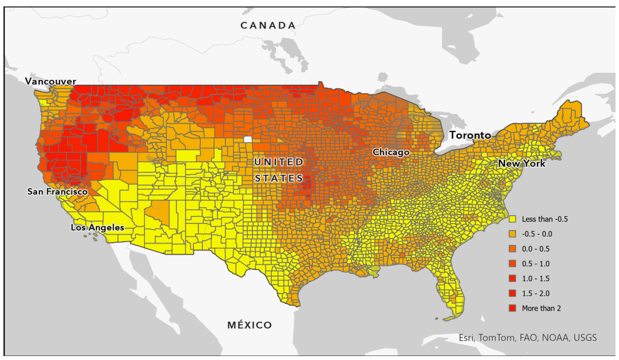
This figures provides time-series statistics on county-level cumulative wildfire smoke exposure and number of smoke days from 2006 to 2020. Annual cumulative wildfire smoke exposure for each county is population-weighted at the census tract-level. A smoke day occurs when more than 75% of the census tracts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



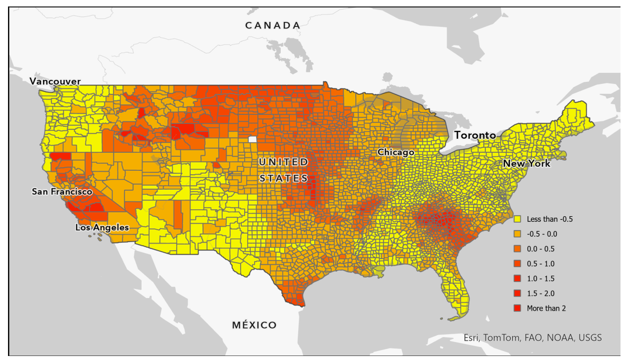
(a) 2010



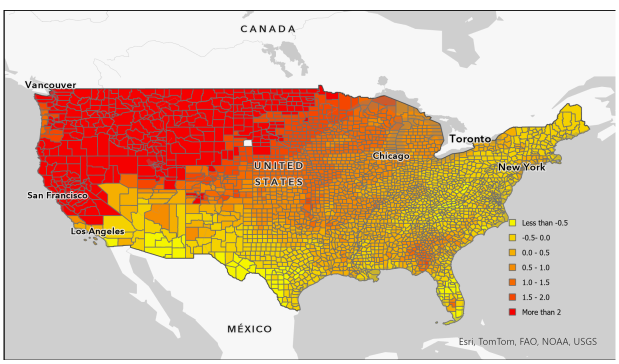
(b) 2012



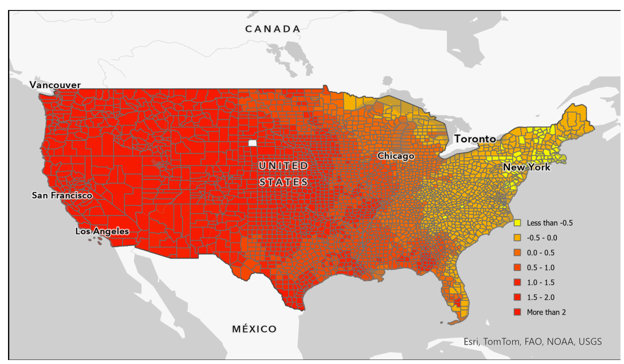
(c) 2014



(d) 2016



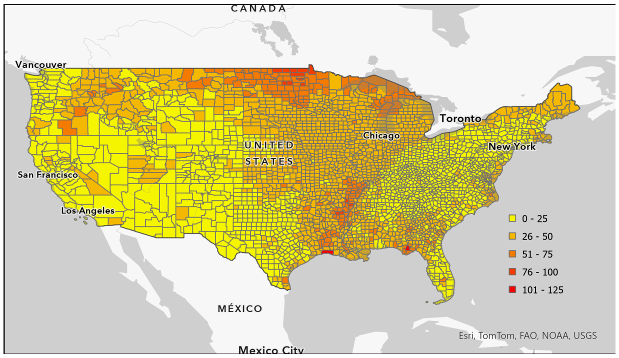
(e) 2018



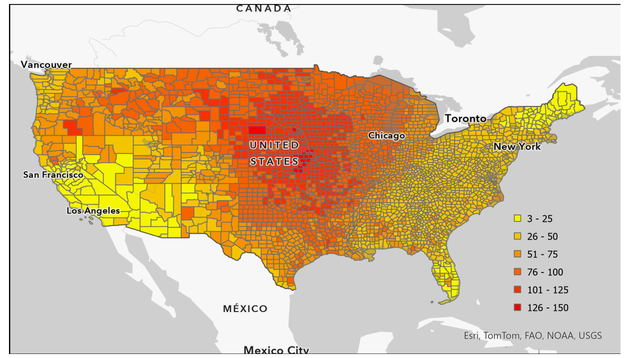
(f) 2020

Figure 2. U.S. Wildfire Smoke Exposure

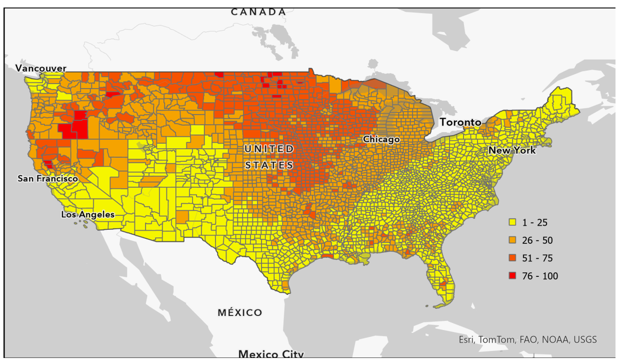
This figure provides heat maps of wildfire smoke intensity for each even year from 2010 to 2020. Wildfire smoke intensity is the standardized population-weighted cumulative amount of smoke $PM_{2.5}$ exposure during the county-year across census tracts, where the standardization is based on the mean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



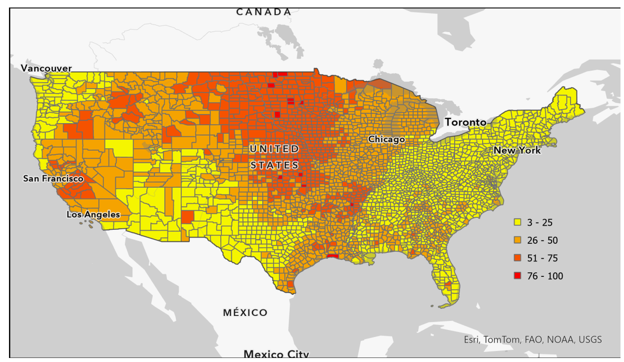
(a) 2010



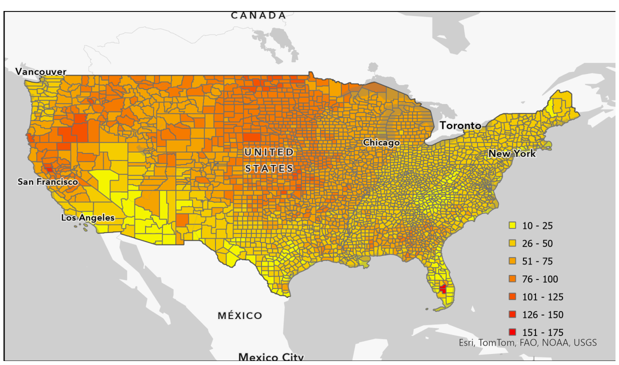
(b) 2012



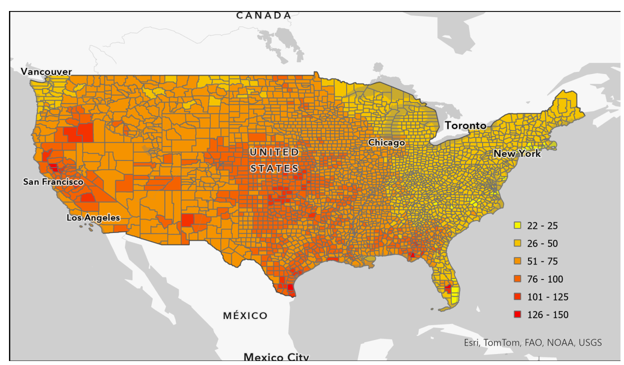
(c) 2014



(d) 2016



(e) 2018



(f) 2020

Figure 3. U.S. Wildfire Smoke Days

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

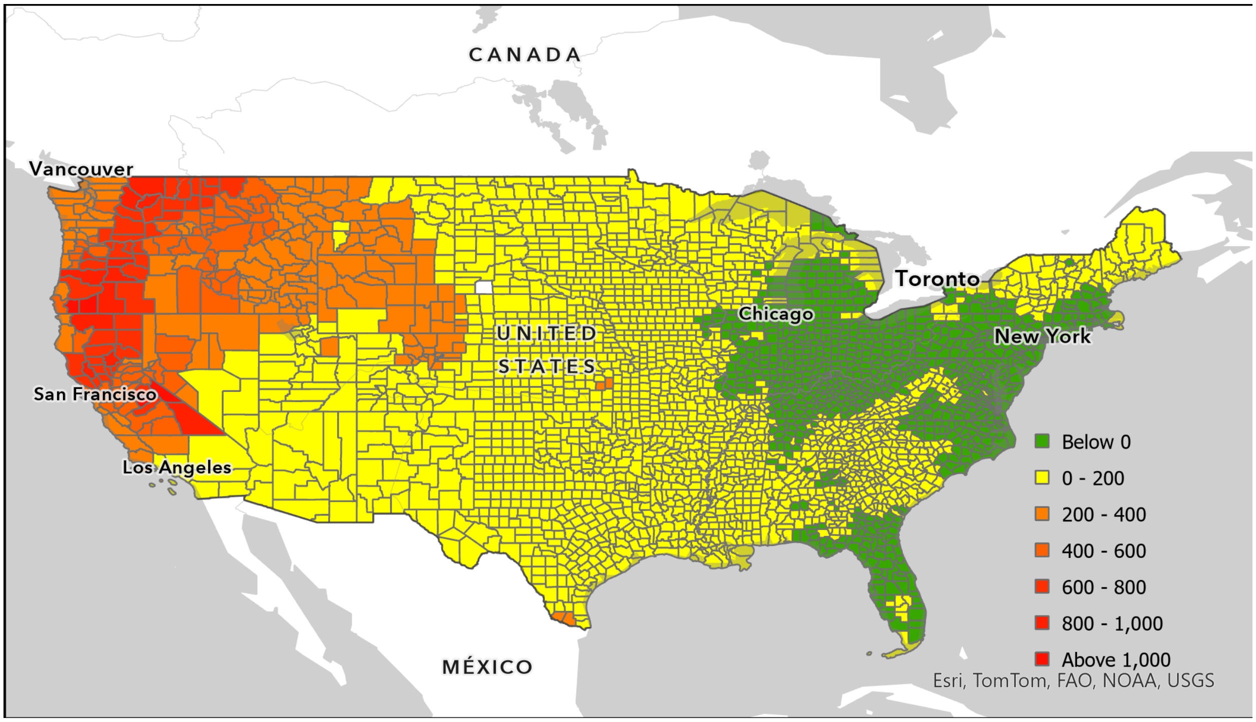


Figure 4. Decennial Change in Annual Cumulative Smoke Exposure (2016-2020 vs 2006-2010)

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

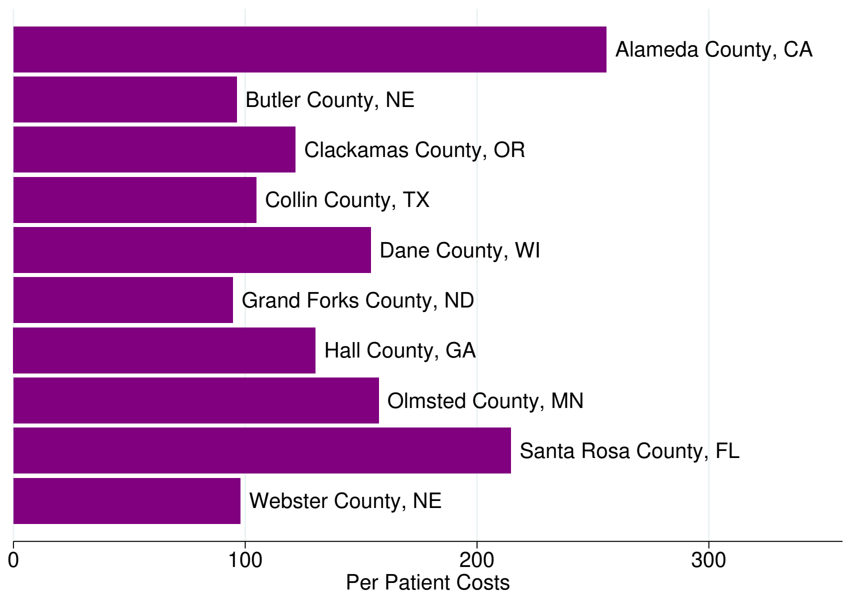


Figure 5. Top Ten Counties by Future Wildfire Pollution Borrowing Costs

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

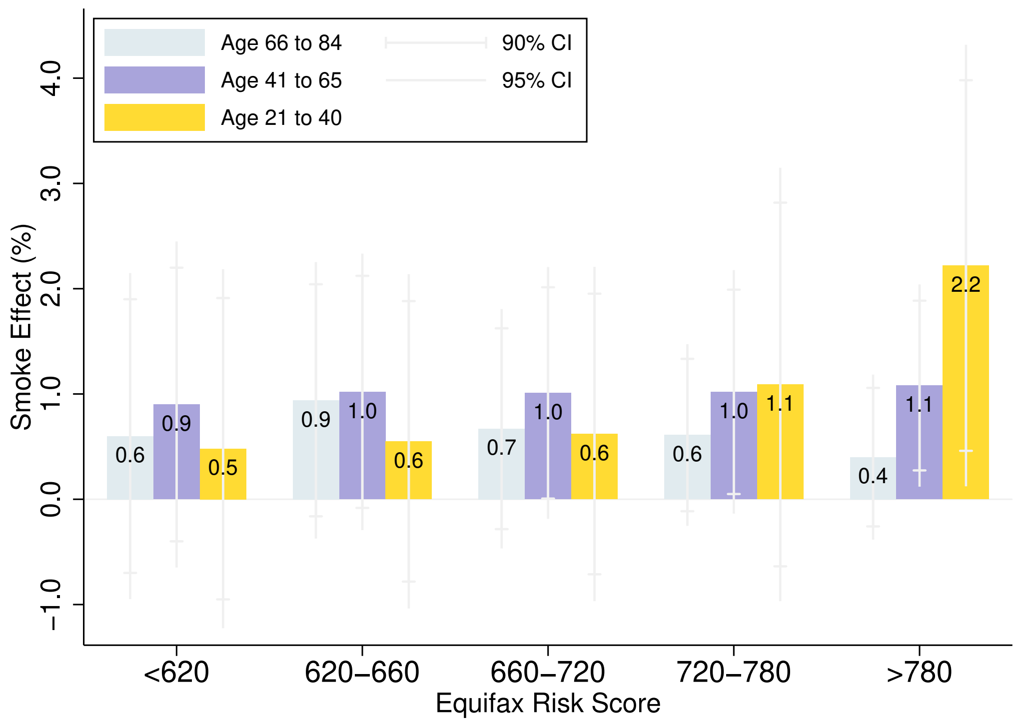


Figure 6. The Effects of Smoke Pollution on Out-Migration by Age and Credit Score

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