Pricing Climate Risks: Evidence from Wildfires and Municipal Bonds[*]

Woongchan Jeon[†] Lint Barrage[‡] Kieran James Walsh[§]

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Abstract

How are financial markets responding to anticipated climate-driven wildfire risk increases? Combining high-resolution meteorological predictions and land use pattern maps with detailed US municipal bond data, this paper finds that municipalities facing higher future wildfire risk increases are already having to pay substantially higher borrowing costs as a result. A one standard deviation increase in future wildfire exposure is associated with a 23-basis point rise in school district bond spreads, corresponding to 42% of the sample mean. Borrowing cost impacts are significantly larger in areas with higher minority population shares and heavier reliance on local revenue sources.

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JEL Classification Codes: G12, H74, Q54

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[†]ETH Zurich; woongchan.jeon@mtec.ethz.ch

[‡]ETH Zurich; lbarrage@ethz.ch

[§]ETH Zurich; kwalsh@ethz.ch

1 Introduction

Wildfires are imposing increasing costs on the US economy. In 2018 alone, the direct costs from wildfire events, measured by the sum of insured and estimated uninsured losses, amounted to $30 billion (in 2024 USD), accounting for 26% of the total damages incurred from climate-related natural disasters in the US (NOAA, 2024). Even costlier are the estimated health impacts of wildfire smoke, which include over 15,000 excess deaths per year (Qiu et al., 2024), over 3,000 additional emergency department visits (Heft-Neal et al., 2023), and significant increases in hospitalizations (Gould et al., 2024). Importantly, the potential for wildfires is expected to rise substantially in many parts of the US due to climate change (Brown et al., 2021). Accordingly, there is growing public concern about the fiscal implications of increasing wildfire risks through channels such as firefighting costs or healthcare spending both at the federal (CBO, 2022; OMB, 2022) and local levels. Indeed, the likelihood of municipal budget deficits has been found to increase by 25 percentage points following historic fire events (Liao and Kousky, 2022). Despite this growing evidence on their potential economic importance, wildfires have received comparatively little attention in the academic literature on the social costs and financial asset capitalization of climate change risks.[1] Recent industry reports also indicate continued skepticism as to whether climatic risks are reflected in municipal bond prices (NYSE: ICE, 2022).

This paper presents what is to the best of our knowledge the first dedicated academic analysis of the capitalization of future wildfire risk changes in US financial markets, specifically municipal bonds.[2] We exploit high-resolution meteorological predictions and granular variations in land use patterns to study whether municipal bond markets reflect climate-induced wildfire risk changes. Building upon the panel regression approach developed by prior literature investigating the capitalization of sea level rise risks into municipal bonds (Goldsmith-Pinkham et al., 2023), we focus on school district bonds in the secondary market.

[1]Wildfire impacts are typically not modeled in climate-economic assessment models and feature limited reflection in leading recent empirical and policy estimates of the social cost of carbon (see, e.g., discussion in EPA 2023).

[2]Smull et al. (2023) study the cross-sectional relationship between municipal bond spreads and a composite commercial climate risk index from Intercontinental Exchange, which includes wildfires jointly with hurricanes, flooding, and other risk factors.

A majority of fixed income securities issued by school districts are general obligation bonds backed by property taxes, which establishes a direct link between local economic conditions and the ability to service debt. Our outcome variables of interest are municipal bond spreads defined by the difference between a bond's yield-to-maturity and a maturity-matched risk-free benchmark yield.

To identify the association between future wildfire risks and credit spreads, we leverage three sources of variation: (1) varying term structures of bonds issued within a given school district, (2) changes in local wildfire risks over time, and (3) increased awareness regarding the perils posed by climate change. Many school districts issue bonds with varying maturities at issuance. If the market is capitalizing future wildfire risks, investors would consider the risk trajectory of a district and price bonds based on the anticipated risk leading up to their maturity dates. Our central estimation regresses municipal bond spreads on historical and future measures of local economic wildfire risk (quantified based on both local physical wildfire risk and the number of housing units in the Wildland Urban Interface where residential structures meet vegetation) and a rich set of control variables. Our controls include bond characteristics as well as district-by-month fixed effects (e.g., Santa Barbara Unified School District in May 2024) and district-by-maturity-date-group fixed effects (e.g., Santa Barbara Unified School District bonds maturing in 2040-44). District-by-month fixed effects help account for economic factors that may be correlated with trends in both wildfire risks and the creditworthiness of a district, whereas district-by-maturity-date-group fixed effects help control for the general effects of future maturity dates on credit spreads within each district.

Our central finding is that future wildfire risks appear to be increasingly capitalized into US municipal bond markets. We observe both statistically and economically significant effects of future wildfire risk increases on bond spreads, with a one standard deviation increase in future wildfire exposure leading to a 23-basis point rise in school district bond spreads post-2014, which is equivalent to 42% of the mean spreads in the sample. The estimated impacts are robust to other estimation methods, spatial coverage, and alternative wildfire measures.

The results are also robust to excluding communities directly affected by wildfire events over our sample period. Delving into heterogeneity, we observe notably higher wildfire risk impacts in districts heavily reliant on local revenue sources post-2014, consistent with a mechanism via local economies and property values, for which we provide additional suggestive evidence as well.[3] We also find that the capitalization of wildfire risks is more pronounced in districts with larger non-white population shares even after accounting for income. In sum, our results indicate that anticipated future wildfire risk changes are already having economically significant impacts on financial markets, municipal borrowing costs, and vulnerable communities.

This paper relates to four main strands of research. First, this analysis contributes to our understanding of how climate risks are capitalized into asset prices. While a larger set of studies has examined the capitalization of "climate risks," broadly defined to include, e.g., regulatory risks or present-day natural disaster risks (see, e.g., Giglio et al. 2021 and Campiglio et al. 2023 for reviews), we specifically contribute to a more nascent body of evidence on the capitalization of not only current but also *future risk changes* from physical climate change. For housing as an asset class, several studies have found evidence of at least partial capitalization of future sea level rise (Bernstein et al., 2019; Baldauf et al., 2020; Bakkensen and Barrage, 2022), though some disagreement remains (Murfin and Spiegel, 2020). Certain future climate risks have also been found to be partially capitalized into equity markets (e.g., drought trends as in Hong et al. 2019, heat stress as in Acharya et al. 2022, and general climate risk indices as in Ling et al. 2023), corporate bonds markets (e.g., heat stress as in Acharya et al. 2022), and land markets (e.g., extreme temperature and precipitation as in Severen et al. 2018). Most closely related to our analysis is the capitalization of future climate risks in the US municipal bond markets, which has been observed for future sea level rise (Painter, 2020; Goldsmith-Pinkham et al., 2023) and future heat stress (Acharya et al., 2022). Several studies have further documented associations between *general* climate risk indices from proprietary sources and both US municipal (Smull et al., 2023)[4] and sovereign (Beirne et al., 2021; Cevik

[3]In the appendix, we document a negative correlation between housing values and future wildfire risk increases in our sample.

[4]Based on a *cross-sectional* analysis, they study the secondary market using *model-generated* spreads from Bloomberg's Evaluated Pricing Service as of April 27, 2022, while their primary market analysis focuses on *observed* spreads derived from transactions

and Jalles, 2022) borrowing costs.[5] To the best of our knowledge, this paper is the first to demonstrate the capitalization of anticipated wildfire risk changes as such into asset prices.

Second, and closely related, this analysis adds to a nascent body of work demonstrating the capitalization of current wildfire risks into financial markets, which to date includes option prices (Ouazad, 2022), prices of mortgage-backed securities (Kahn et al., 2024), property insurance premiums (Boomhower et al., 2024), and bank portfolios (Ouazad and Kahn, 2022). Several recent studies have also used broad measures of historic natural disaster exposure that may include wildfires to demonstrate the overall impacts on financial market outcomes, including insurers' stock returns (Jung et al., 2023) and municipal bond returns (Auh et al., 2022).[6] We contribute to this literature by studying the municipal bond pricing impacts of current and climate-driven future wildfire risks.

Third, this paper relates to a relatively new body of literature that quantifies the economic impacts of wildfires. The literature on environmental economics has quantified the direct impacts of historic wildfire and smoke events on outcomes such as structure survival rates (Baylis and Boomhower, 2022), employment and income (Borgschulte et al., 2022; Walls and Wibbenmeyer, 2023; Roth Tran and Wilson, 2023), local business activities (Addoum et al., 2024a), crop yields (Behrer and Wang, 2024), student test scores (Wen and Burke, 2022), and outdoor recreational activities (Gellman et al., 2023), in addition to well-established adverse health impacts (Wen et al., 2023; Qiu et al., 2024). The literature on consumer finance has recently quantified the direct costs of wildfire events on household balance sheets through consumer credit outcomes (McConnell et al., 2021), mortgage repayment (An et al., 2024; Biswas et al., 2023; Issler et al., 2024), and student loans (Cornaggia et al., 2023a). Finally, several studies on real estate markets have linked present-day wildfire risks to housing prices using spatially discontinuous hazard map updates (Ma et al., 2024; Garnache, 2023),

at issuance. In contrast, our analysis adopts a panel regression approach using observed municipal credit spreads in the secondary market.

[5] Several recent studies, such as Mallucci (2022) and Phan and Schwartzman (2023), have used quantitative models to project the impacts of changing climate risks on sovereign bond markets, focusing on tropical cyclone risks in the Caribbean countries and Mexico, respectively.

[6] These studies use the Spatial Hazard Events and Losses Database for the United States (SHELDUS), which encompasses various natural disaster events including but not limited to wildfire events. Globally, other studies have considered the impacts of disasters such as floods on sovereign bond markets (Klomp, 2017).

historic wildfire events (McCoy and Walsh, 2018), and exposure to smoke plumes (Huang and Skidmore, 2024; Addoum et al., 2024b).

A fourth related strand is the emerging literature examining the fiscal perils associated with climate-related disasters. For example, Jerch et al. (2023) document the adverse impacts of hurricane strikes on several US municipal fiscal outcomes and note that these impacts are larger in communities with larger non-white population shares. Our findings of unequal future wildfire risk capitalization add to these insights. While a growing literature investigates the impacts of different climatic risks,[7] there exists a distinct concern regarding the escalating fiscal burden resulting from wildfire risks (CBO, 2022; OMB, 2022). Recent studies have evaluated rising expenditures on specific programs directly related to fire events, such as wildfire suppression costs (Wibbenmeyer et al., 2019; Plantinga et al., 2022; Baylis and Boomhower, 2023) and Medicare spending (Miller et al., 2017). Notably, Liao and Kousky (2022) focus on the impact of historic fire events on aggregated municipal fiscal outcomes. But none of them explores the rising borrowing costs that may arise due to wildfire risk. Our analysis uncovers a potential vicious cycle in which school districts facing larger future wildfire risks could experience lower provision of public goods due to increasing borrowing costs. Reduced fiscal space could, in turn, hamper future disaster recovery (Phan and Schwartzman, 2023) or lead to further unintended consequences, such as hindered human capital accumulation (Park et al., 2020; Biasi et al., 2024).

The remainder of this paper proceeds as follows. Section 2 delineates our methodology for quantifying future economic wildfire risk. Additionally, we describe the municipal bond data and historic fire perimeters. In Section 3, we discuss our identification strategy and empirical results on the capitalization of future wildfire risk changes on municipal credit spreads. Section 4 concludes.

[7] In the United States, this literature has considered fiscal impacts of hurricanes (Deryugina, 2017; Jerch et al., 2023), temperature extremes (Barrage, 2024), and general disasters (Miao et al., 2018).

2 Data

2.1 Economic wildfire risks

From an economic perspective, wildfire risk encompasses two factors: physical wildfire risk, based on meteorological conditions, and the presence of valuable assets, such as residential structures in proximity to vegetative fire fuels. To quantify wildfire potential based on this intuition, we rely on two data sources. First, Brown et al. (2021) compute the Keetch–Byram Drought Index (KBDI) across the contiguous United States, which is calculated at a spatial resolution of 12 km for both historic (1995-2004) and mid-century (2045-2054) periods. It is based on weather predictions from a climate model under a high emissions scenario.[8] The KBDI is a widely-used metric for assessing meteorological conditions related to wildfire events using factors such as daily maximum temperature, daily precipitation, and annual accumulated precipitation (Keetch and Byram, 1968).

The US Global Change Research Program (USGCRP) divides the contiguous United States into seven regions to evaluate region-specific climate risks in its National Climate Assessment: Northwest (NW), Southwest (SW), Northern Great Plains (NGP), Southern Great Plains (SGP), Midwest (MW), Northeast (NE), and Southeast (SE) (USGCRP, 2017).[9] We restrict our sample to regions that have historically experienced KBDI values indicative of a high potential for wildfire events ($>$ 400 in the period from 1995-2004, Liu et al. 2010), specifically the NW, SW, and SGP regions. We provide a robustness check on our main regression by including other regions. To count the number of housing units exposed to different KBDI levels, we overlay 12 km resolution KBDI polygons with 2010 US census blocks, which represent the smallest geographical units used by the Census Bureau for housing data tabulation during its decennial census.

[8] Brown et al. (2021) use the Weather Research and Forecast (WRF) simulations driven by Community Climate System Model (CCSM) version 4 under the Representative Concentration Pathway 8.5 (RCP 8.5), which assumes high levels of greenhouse gas emissions by the end of this century (Riahi et al., 2011).

[9] See Table A1 for the grouping of states by region.

Second, Radeloff et al. (2018) categorize US census blocks into two groups based on whether their residential structures intersect with wildland vegetation, using housing data from the 2010 Decennial Census and the National Land Cover Data from the US Geological Survey. This classification, known as the Wildland-Urban Interface (WUI), helps local communities identify areas where wildfires can pose risks due to their proximity to vegetative fuels. To link meteorological conditions relevant to wildfire potential with available fuel sources, we integrate WUI status into the KBDI assessment. For example, a census block in downtown Los Angeles may exhibit a high level of KBDI by mid-century. However, accounting for its WUI status could reduce its fire potential to zero, as there is little flammable vegatation.[10]

To evaluate the fire risk of each bond issuer, we aggregate the KBDI and WUI data from the census block level to the school district level in the following way. For a given school district d, let N_d represent the number of census blocks intersecting with the district. Within each block i, data on the number of housing units (HU) and the WUI classification is available. We compute the weighted KBDI for both historic and mid-century periods, using the number of housing units in the wildland-urban interface areas as weights: for $p \in \{\text{historic}, \text{mid-century}\}$,

$$\textsc{Weighted KBDI}_d(p) = \sum_{i=1}^{N_d} \left[\frac{\text{HU}_i}{\sum_{j=1}^{N_d} \text{HU}_j} \times \text{KBDI}_i(p) \times \mathbb{I}(i = \text{WUI}) \right]. \tag{1}$$

Figure 1 maps the historic and mid-century weighted KBDI, along with their difference, in the Northwestern, Southwestern, and Southern Great Plains regions. In general, the Southwestern region exhibits high risk levels for both the historical and mid-century periods. But the Southern Great Plains area additionally stand out when considering the difference. We also consider alternative measures of future wildfire potential from two additional sources.[11]

[10]Indeed, Gannon and Steinberg (2021) find a positive correlation between fire occurrences and corresponding risk measures on a global scale, which take into account both meteorological conditions and land cover but at a coarser resolution (1/4°) than Brown et al. (2021).

[11]Kearns et al. (2022) compute the cumulative likelihood of wildfire occurrences exceeding 14% over the next 30 years relative to 2023 using the RCP 4.5 scenario. ANL (2023) calculates the ensemble mean of the seasonal average daily Fire Weather Index (FWI) — a wildfire risk index developed by the Canadian Forest Service — using Argonne's downscaled 12 km climate data under RCP 8.5. We find a strong correlation of 0.59 and 0.70 at the school district level in our sample between the difference in the weighted KBDI and the two alternative measures, respectively. We provide a robustness check using the latter data for our main regression. For details, refer to Appendix A.

[Figure 1 Here]

2.2 Bond transactions and characteristics

We use the Refinitiv Data Platform APIs to extract bond characteristics of US school districts. We filter municipal bonds where their purpose is classified as "Primary or Secondary Education" and their federal tax status is marked as "Exempt." Our secondary market transaction data are from the Municipal Securities Rulemaking Board (MSRB) Academic Historical Transaction Data, covering trades from 2005 to 2020 (our data access cutoff year). We then merge these datasets using the 9-digit Committee on Uniform Securities Identification Procedures (CUSIP) number.

Municipal bond issuers often pre-refund their bonds prior to their call date by issuing new debt and holding the proceeds in US government securities to cover remaining payments until their call date. We exclude transactions of bonds labeled as "pre-refunded," as they are essentially risk-free (Chalmers, 1998). The changes in sample size resulting from this and other data processing steps are delineated in Table 1. Following Green et al. (2010), we address clerical errors by excluding trades without prices, those occurring on holidays or weekends, those priced above \$150 or below \$50 per \$100 par value, and those with coupon rates exceeding 20%. To ensure a sufficient level of liquidity, we limit our sample to bonds that were traded at least 10 times during our sample period (Schwert, 2017). We remove trades during the first three months after the issuance and during the last year before the maturity as these transactions are noisy (Green et al., 2007). We exclude trades with a time-to-maturity greater than 30 years as our benchmark yield curve for credit spread calculation spans from 1 to 30 years.

In municipal bond markets, trades occur infrequently, and intraday price fluctuations can be substantial compared to changes in fundamentals due to differing terms among various types of investors (Green et al., 2007). Therefore, following Green et al. (2010), we aggregate transaction data on a daily frequency by computing the midpoint between the lowest price at which dealers sell to customers and the highest price at which dealers purchase from customers. If both of them are not observed on a given day, we use the average price of all interdealer transactions. If neither method is applicable, we exclude the data (Schwert, 2017). We construct a monthly panel by taking the arithmetic mean of daily fundamental prices in a given month and compute the yield to maturity. To calculate credit spreads, we match the yield to maturity of a bond with its maturity-matched Municipal Market Analytics (MMA) municipal yield benchmarks obtained from the Bloomberg Terminal, based on the last date a trade occurred each year-month following Goldsmith-Pinkham et al. (2023).

We then match bond data to wildfire risk data. To tabulate wildfire risks by school districts, we use the Institute of Education Sciences National Center for Education Statistics (NCES) school district boundaries that can be uniquely identified with Local Education Agency Identification (LEAID) numbers. We match the LEAID with the 6-digit CUSIP, which uniquely corresponds to bond issuers. Details of our name matching procedure are provided in the appendix B.

In our baseline regression, we account for potential countywide interdependence in local economic conditions by clustering standard errors at the county level. But some school districts in the sample overlap more than one county. We overlay the NCES school district boundaries with the US Census county shapefiles to identify their geographic relation in the 2010 vintage. We then restrict our sample to bonds issued in counties that contain more than one district without overlaps. We provide a robustness check on our main regression by including bonds issued in school districts that span across two counties and clustering standard errors at the district level.

2.3 Maturity year-matched future wildfire risks

In contrast to sea level rise, wildfires pose risks both in the near and far future. Abatzoglou and Williams (2016) find that climate change has heightened fuel aridity across Western US forests from 1979 to 2015, correlating with increased wildfire occurrences. Additionally, Brown et al.

(2021) observe a rising trend in annual mean KBDI over forested regions in the Southwestern and Northwestern US since 1982 as well. Both indicate a persistent drying trend, which could potentially exacerbate fire activities, even in the near future. Appendix Figure A1 displays the distribution of time-to-maturity in years for the bonds traded each year. The maturity calendar dates in the sample range from 2006 to 2051. To leverage the variation in fire risks over time *within* a district, we match wildfire risks based on the maturity date of a bond.

We first group maturity calendar dates into intervals of 5 years. For a bond b issued by a district d, let $m(b)$ denote the group to which its maturity calendar date belongs:

$$m(b) = \begin{cases} 0 & \text{if its maturity calendar date falls between 2005 and 2009,} \\ 1 & \text{if its maturity calendar date falls between 2010 and 2014,} \\ \cdots & \\ 8 & \text{if its maturity calendar date is after 2045.} \end{cases} \tag{2}$$

We then interpolate the weighted KBDI using a stepwise function with equal steps from the historic (1995-2004) to mid-century (2045-2054) levels. For a bond b issued by a district d,

$$\begin{aligned} &\textsc{Weighted KBDI}_{d,m(b)} = \textsc{Weighted KBDI}_d(\text{history}) \\ &+ \big[\ \textsc{Weighted KBDI}_d(\text{mid-century}) - \textsc{Weighted KBDI}_d(\text{history})\ \big] \times \frac{m(b)}{8}. \end{aligned} \tag{3}$$

We then define the maturity-calendar-date-group-matched wildfire risk change as the difference between the maturity-calendar-date-group-matched interpolated value and the historical level:

$$\Delta\textsc{Fire}_{d,m(b)} = \textsc{Weighted KBDI}_{d,m(b)} - \textsc{Weighted KBDI}_d(\text{history}). \tag{4}$$

We conduct a robustness check on our main regression by varying the step size from 5 years to 2 and 8 years.

Table 1 summarizes the sample construction and provides summary statistics.

[Table 1 Here]

After winsorizing at the 1% level, spreads vary from -61.16 to 279.62 basis points. The average time to maturity is 7.70 years, and the average increase in the weighted KBDI is 10.57. The sample comprises 406,647 bond-month trades spanning from 2005 to 2020, with 52,280 bonds issued by 1,641 school districts. The mean (median) number of bonds traded in a district-year-month is 3.60 (2). Appendix Table A2 presents the sample composition, breaking down each bond's trade by its issuing state and trading year. Bonds issued in California and Texas, or those traded in the later 2010s, are overrepresented. Thus, we provide a robustness check by weighting each bond by the inverse of the count of distinct bonds within each state for a specific trade year.

2.4 Historic wildfire perimeters

In this paper, we study how future wildfire risks are priced in the municipal bond market. But throughout our sample period, a number of wildfires burned across the US. Indeed, Liao and Kousky (2022) document that the probability of municipal budget deficits increases in the aftermath of wildfires in California. Moreover, there is burgeoning empirical evidence on the direct costs of historic wildfire events on real estate, consumer credit, and the labor market, which could potentially weaken municipalities' ability to service debt and impact bond prices. To isolate the capitalization of future fire risks from the direct impacts of historic fire events, we exclude observations that were directly affected by such events in our robustness check.

To identify school districts affected by large-scale fires, we use the Monitoring Trends in Burn Severity (MTBS) data provided by the US Geological Survey Earth Resources Observation and Science center and the US Department of Agriculture Forest Service Geospatial Technology and Applications center. This dataset is available from 1984 to present. We overlay the MTBS wildfire footprint polygons with the 2010 US census blocks to locate census blocks impacted by historic wildfire events. For a given school district d, let N_d represent the number of census blocks within the school district. Within each block i, data are available on the number of housing units (HU) and whether the block experienced wildfire events. We then compute the percent of housing units affected by historic wildfires at the school district levels as follows:

$$\frac{1}{\sum_{j=1}^{N_d} \mathrm{HU}_j} \times \sum_{i=1}^{N_d} \Big[\mathrm{HU}_i \times \mathbb{I}(i \text{ is in the MTBS fire footprint}) \Big]. \tag{5}$$

We filter events that occurred after 2005 to match municipal bond transaction data. We then define school districts impacted by large-scale wildfire events as those where more than 0.1% of housing units were affected for the first time during our sample period. We provide a robustness check by excluding all the transactions from school districts since they were first impacted by large-scale wildfire events, which amounts to 79,250 bond-month observations.

2.5 Socioeconomic and municipal finance data

We collect socioeconomic and municipal finance data for all school districts for heterogeneity analysis. First, the National Center for Education Statistics (NCES) Education Demographic and Geographic Estimates (EDGE) program uses the Census Bureau's American Community Survey (ACS) to summarize socioeconomic information for each district. We collect data on median household income and the percentage of the population identifying as white to examine whether districts with higher minority population shares face higher borrowing costs in response to an increase in future wildfire risks. Second, our municipal finance data is from the NCES Common Core Data (CCD) School District Finance (SDF) survey, which provides the data on school district finances. We focus on revenues to determine whether districts with a greater reliance on local revenue sources incur higher interest rates in response to rising wildfire risks. We then merge these datasets with our bond data using the Local Education Agency Identity (LEAID).

3 Empirical methods and results

3.1 Identification strategy

To identify the association between future wildfire risk changes and municipal bond credit spreads, we adopt the following regression specification:

$$\textsc{Spread}_{b,d,c,t} = \lambda_{d,t} + \alpha_{d,m(b)} + \sum_{\substack{y=2005 \\ y\neq 2006}}^{2020} \mathbb{I}(\textsc{Year} = y) \ \left[\beta_y \Delta\textsc{Fire}_{d,m(b)} + \boldsymbol{\theta}'_y \mathbf{Z}_{b,d,c,t}\right] + \boldsymbol{\gamma}'\mathbf{X}_{b,d,c,t} + \varepsilon_{b,d,c,t}, \tag{6}$$

for the transaction of bond b, issued by school district d within county c and occurring in year-month t. We define Spread as the yield to maturity over its maturity-matched MMA municipal yield benchmark on the last date a trade occurred each year-month for that bond. Maturity calendar dates are grouped into intervals of 5 years, and wildfire risks are interpolated using a stepwise function with equal steps from the historic level (1995-2004) to the mid-century prediction (2045-2054). We define ΔFire as the difference between the maturity calendar date group-matched interpolated value and the historic level, which is now standardized to a mean of zero and standard deviation of one. The covariates in $\mathbf{Z}$ include the natural logarithm of the number of years before the maturity date (time to maturity in years) and insurance status to account for time-varying term premia and the evolution of municipal bond insurance value (Chun et al., 2019; Cornaggia et al., 2023b). Other covariates in $\mathbf{X}$ include each bond's age in years, its monthly trading volume divided by its face value (turnover), the monthly standard deviation of its prices, as well as its callability and sinkability status.

We also include the bond's district-by-maturity-calendar-date-group fixed effects $\alpha_{d,m(b)}$ to absorb any time-invariant differences across bonds with varying maturity calendar dates within the same district. For example, bonds maturing at later years may inherently carry greater credit risks compared to those with earlier maturity dates within a district. Additionally, we include district-by-trade-year-month fixed effects $\lambda_{d,t}$ to control for any time-varying local economic conditions and issuer credit ratings, which helps account for factors that may correlate with trends in wildfire risks and the creditworthiness of a school district. Standard errors are clustered at the county level to account for within-county interdependence in local economic conditions. We put equal weights to each bond-year-month observation.

In line with Goldsmith-Pinkham et al. (2023) and Acharya et al. (2022), we hypothesize that awareness of future climate perils increases over time, following the release of the IPCC's fifth assessment report in 2014. The main coefficient of interest β_y measures the year-to-year within-district variation in spreads in response to a one standard deviation increase in wildfire risk changes relative to the reference year. To summarize impacts after 2014, we adopt the following specification:

$$\begin{aligned}\textsc{Spread}_{b,d,c,t} = {} & \lambda_{d,t} + \alpha_{d,m(b)} + \beta\ \mathbb{I}(\textsc{Year} \geq 2015)\Delta\textsc{Fire}_{d,m(b)} \\ & + \sum_{\substack{y=2005 \\ y\neq 2006}}^{2020} \mathbb{I}(\textsc{Year} = y)\boldsymbol{\theta}_y'\mathbf{Z}_{b,d,c,t} + \boldsymbol{\gamma}'\mathbf{X}_{b,d,c,t} + \varepsilon_{b,d,c,t},\end{aligned} \tag{7}$$

where the trade year indicators are replaced by $\mathbb{I}(\textsc{Year} \geq 2015)$, which equals one for all periods post-2014 and zero otherwise. The parameter β summarizes the average effect after 2014. The other covariates are identical to those specified in Equation 6.

3.2 Main results

Table 2 presents the year-by-year and post-2014 impacts of wildfire risk changes on the credit spreads of school district bonds. In column (1), our regression analysis adopts parsimonious controls by including district-by-trade-year-month fixed effects to address time-varying local economic conditions. In column (2), we further control for district-by-maturity-calendar-date-group fixed effects to account for any time-invariant differences across bonds with varying term structures within the same district. In column (3), our benchmark regression specification additionally incorporates controls for bond-level characteristics.

[Table 2 Here]

In the most parsimonious specification, we observe a positive association between future wildfire risk changes and credit spreads in the baseline year (2006). This positive correlation can be partly attributed to the varying term structures of bonds issued by the same school district; bonds with later maturity calendar dates could inherently carry higher time-invariant risks compared to those maturing sooner. After adjusting for district-by-maturity-calendar-date-group fixed effects to account for such confounding factors, we see that the impact of future wildfire risk changes on credit spreads within the same district begins to diverge since 2010. However, this positive association could be resulting from time-varying bond-level characteristics such as term premia or the value of bond insurance. In particular, Chun et al. (2019) and Cornaggia et al. (2023b) document that the creditworthiness of municipal bond insurers declined following the Great Recession, and the benefits of insurance dissipated in both secondary and primary markets.

After accounting for bond-level characteristics, the positive correlations diminish, and the yearly variation in spreads from 2010 to 2014 becomes statistically indistinguishable from the baseline trade year. Similar to the findings in Goldsmith-Pinkham et al. (2023) and Acharya et al. (2022), we observe positive yearly coefficients around the release of the fifth IPCC report, which suggests that the difference in spreads among bonds with varying maturities within the same district begins to widen further in the mid-2010s compared to 2006. On average, a one standard-deviation increase in the weighted KBDI leads to a 23-basis point rise in school district bond spreads post-2014, which is about 42% of the average spreads in the sample.

Figure 2 plots the year-by-year estimates in column (3). The rise in wildfire risk premiums in US school district bond markets coincides with some evidence regarding the increasing fire activities in the US. Burke et al. (2021) find that burned area from wildfires has quadrupled over the past four decades in the US. Moreover, Abatzoglou and Williams (2016) document that anthropogenic climate change substantially increased fuel aridity in Western US forests during 2000-2015. Combined with increased fire activities, the release of the fifth IPCC report in 2014 may have heightened awareness of wildfire potentials within financial markets.

[Figure 2 Here]

3.3 Robustness

We conduct several robustness checks on our main regression by adopting different estimation methods, expanding spatial coverage, using an alternative metric for wildfire risks, excluding communities directly impacted by wildfire events during our sample period, and varying the step size for interpolating future wildfire risks within districts. First, we assign weights to bond-trade-year-month observations by the inverse of the count of distinct bonds within each state for a specific year. We use this new weight because bonds issued in California and Texas, or those traded in the later 2010s, are overrepresented in our sample (see Table A2). Column (2) in Appendix Table A3 reports the year-by-year and post-2014 impacts using equal weights. The post-2014 average impact of wildfire risk on municipal spreads is approximately 1 basis point higher, but the year-by-year patterns are qualitatively similar.

Second, we expand our sample by including bonds issued in counties that either contain only one district or span across two counties to improve the representativeness of our sample. The number of bonds and districts in our sample increases from 52,280 to 68,780 and 1,641 to 2,458, respectively. With this expansion, school districts are not nested within counties, and thus, we cluster standard errors at the school district level. Columns (3) and (4) in Appendix Table A3 present the year-by-year and post-2014 impacts after including these instances. The former does not use equal weights, while the latter does. The average impact post-2014 is higher, but the year-by-year patterns remain qualitatively similar to those observed in the benchmark regression.

Third, we expand the spatial coverage of our sample by including the Northeast, Southeast, Midwest, and Northern Great Plains regions. Appendix Table A4 replicates the main regression analysis with this expanded sample. While the year-by-year estimates exhibit similar patterns, the average impact post-2014 is smaller than the benchmark regression. The impact on credit spreads is smaller because the extended regions have meteorological conditions that are less prone to wildfires (Brown et al., 2021), meaning that a one standard deviation rise in future wildfire risk represents a smaller increase than in our benchmark specification.

Fourth, we use the Fire Weather Index (FWI) calculated by ANL (2023) as an alternative metric for assessing wildfire risks. Specifically, we apply the same weighting methods outlined in Section 2 to the Summer average daily FWI, as the index reaches its peak during this season, to quantify the future wildfire risks for each district (see Appendix A for details). Panels (c) and (d) in Appendix Figure A2 map the spatial distribution of the weighted FWI across the contiguous US. The correlation between the weighted KBDI and the weighted FWI in our final sample is 0.70. Appendix Table A5 replicates our main regression analysis using the weighted FWI. Both the year-by-year and post-2014 estimate exhibit the same pattern.

Fifth, we exclude observations starting from the year-month in which they were first affected by large-scale fire events to isolate the capitalization of future fire risks from the direct impact of historic wildfires. Appendix Table A6 replicates the main regression analysis using the sample without directly affected communities. The year-by-year estimates exhibit similar patterns.

Lastly, we vary the step size used for interpolating future wildfire risks. Appendix Table A7 replicates the main regression analysis using step sizes of 2 and 8 years. The year-by-year patterns remain qualitatively similar.

3.4 Heterogeneity and further analysis

We examine whether there exist any unequal impacts of wildfire potential on credit spreads. We first test whether credit spreads are higher for districts with a greater reliance on local revenue sources, as would be expected if the estimated impacts reflect risks to future property values (Auh et al., 2022; Goldsmith-Pinkham et al., 2023). To implement the heterogeneity analysis, we categorize school districts into two groups: one with its own historical average ratio of local to total revenue greater than the national mean, and the other with a ratio below the national mean. We interact this indicator with wildfire risk changes in Equation 7.

Column (2) in Table 3 reports the post-2014 impact of wildfire risk changes on municipal spreads, interacted with the indicator of school districts heavily dependent on local sources. The national average ratio of local to total school district revenue from 2005 through 2021 is about 40%. About 50% of bond-month trades in our sample are issued by districts classified as locally dependent. One standard deviation increase in the weighted KBDI results in an 18.1-basis point increase in municipal spreads post-2014 for districts where less than 40% of revenues are from local sources. Locally dependent school districts face a 29.3-basis point rise in credit spreads in response to a one standard deviation in the weighted KBDI. This finding indicates that investors demand larger spreads for at-risk bonds backed by less diversified tax revenue sources.

[Table 3 Here]

We also examine whether school districts with a higher percentage of minorities face higher interest rates in response to future wildfire risks, motivated by Jerch et al. (2023)'s findings that the municipal fiscal impacts of hurricane strikes are more pronounced in such communities. We categorize school districts into two groups: one with its own historical ratio of nonwhite population greater than 35%, and the other with a percentage less than 35%. The white alone population account for about 70% and 60% in the United States in the 2010 and 2020 Census, respectively. We choose the midpoint as a threshold and about 40% of bond-month trades in our sample are issued by districts classified as high minority share. We further control for district-wide income levels to mitigate their potential confounding effects on distributional outcomes. The nationwide average median household income by school district from 2009 to 2021 is about $58,107 (in 2017 USD). We classify school districts as "High Income" if their own average median household income is above $58,107 (in 2017 USD). Our finding in column (3) of Table 3 shows that a one standard deviation increase in the weighted KBDI leads to an 18.7-basis point increase in credit spreads post-2014 for districts where less than 35% of the population identifies as non-white. School districts with higher minority shares experience a 30.2-basis point increase in municipal spreads following a one standard deviation increase in the weighted KBDI, which remains robust even after controlling for income levels. Taken together, considering both fiscal structure and racial composition is essential to identify vulnerable communities.

Finally, in appendix C, we provide some suggestive evidence on the capitalization of future wildfire risk increases into housing values. If residents are forward-looking, growing wildfire risks should be reflected in property values which, in turn, could affect the value of tax bases and alert lenders to credit risks related to climate change. While identification is more challenging for this outcome (as we cannot include the same set of fixed effects as in our main estimation), we find that higher increases in a district's future fire risks appear to be associated with significant reductions in property values as well.

4 Conclusion

This paper examines whether financial markets are responding to projections of climate-driven wildfire risk changes. We ask this question in the context of the US municipal bond market and wildfire risks, where policy makers have shown increasing concern,[12] but little is know about their impacts empirically. Our main result is that increases in projected wildfire risks over the next 30 years are already associated with economically significant increases in municipal borrowing costs. The emergence of this association in the mid-2010s coincides with increased capitalization of other climatic risks into US municipal bond markets, including sea level rise (Goldsmith-Pinkham et al., 2023) and heat stress (Acharya et al., 2022), suggesting that these trends are not limited to a specific type of climatic risk. At the same time, our results also demonstrate the importance of studying different climate risk factors individually, as prior work considering wildfires only as part of general climate risk indices has often failed to detect economically significant impacts, such as we see in our analysis.

[12] "Investing in the Future: Safeguarding Municipal Bonds from Climate Risk (Full Committee Hearing on Wednesday, January 10, 2024, 10:00 AM)," United States Senate Committee on the Budget https://www.budget.senate.gov/hearings/investing-in-the-future-safeguarding-municipal-bonds-from-climate-risk. Accessed on 2024-10-08.

We also find that future wildfire risk changes have larger effects on districts with higher minority population shares and more reliance on local revenue sources. These findings add to the emerging evidence on the disproportionate fiscal costs of climate change facing lower-income and minority populations (e.g., Jerch et al., 2023; Barrage, 2024; Miao et al., 2023). Our results also suggest the risk of a "vicious cycle," where greater wildfire risk may reduce vulnerable municipalities' fiscal space and, thus, their ability to provide public goods and disaster recovery, further undermining their ability to borrow in the future. Similar risks have been recently pointed out in the international context for disaster-prone emerging markets, where both policymakers and scholars are exploring risk-sharing financial innovations (e.g., Mallucci, 2022; Phan and Schwartzman, 2023). Whether and which risk-sharing innovations could aid US municipalities facing growing climate risks is thus an important area for future research.

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Panel A: Steps to Cleaning Municipal Bond Transaction Data

	Number of Trades
Full MSRB sample	145,451,842
Select federally tax-exempt school district bonds	23,062,421
Drop pre-refunded bonds	13,517,019
Remove clerical errors and select bonds traded at least 10 times	12,248,508
Drop bonds with a time to maturity greater than 30 years	12,188,308
Drop trades during the last year before maturity	11,355,720
Drop trades during the first three months after the issuance	8,161,606
Construct a monthly panel and merge with MMA benchmark yield	1,269,703
Merge with wildfire exposure and other socioeconomic data	1,141,075
Select bonds issued in counties with more than one school district	782,689
Select bonds issued in the NW, SW, and SGP regions	406,647

Panel B: Summary Statistics

	Mean	Standard Deviation	Observations
Fire Risk Change	10.57	14.59	406,647
Yield-to-Maturity (%)	2.38	1.22	406,647
Spread (basis points)	53.65	62.28	406,647
Time to Maturity (years)	7.70	6.22	406,647
Bond Age (years)	3.06	2.74	406,647
Monthly Trading Volume ($000)	599,815.48	2,659,602.90	406,647
Monthly Turnover	0.22	0.45	406,647
Monthly Standard Deviation of Price	0.62	0.66	406,647
$\mathbb{I}\{\text{Insured}\}$	0.35	0.48	406,647
$\mathbb{I}\{\text{Callable}\}$	0.42	0.49	406,647
$\mathbb{I}\{\text{Sinkable}\}$	0.09	0.28	406,647

Table 1: Sample Construction

This table summarizes the sample construction. Panel A outlines the process of cleaning the municipal bond data. Potential clerical errors include trades without prices, those occurring on holidays or weekends, those priced above $150 or below $50 per $100 par value, and those with coupon rates exceeding 20%. See Section 2 for information on each step. The final sample comprises 406,647 bond-month trades spanning from 2005 to 2020, with 52,280 bonds issued by 1,641 school districts. Panel B reports the summary statistics for the variables used in the sample. Fire Risk Change is the difference between the maturity-calendar-date-group-matched interpolated weighted KBDI and the historical weighted KBDI within a district. Yield-to-Maturity is an annual interest rate that equates the present value of cash flow payments received from a bond with the monthly mean of its daily fundamental prices. Spread is the yield-to-maturity above the maturity-matched MMA benchmark yield. Time to Maturity is the number of years between the transaction date and the maturity date in the bond-year-month. Bond Age is the number of years between the issue date and the transaction date in the bond-year-month. Monthly Trading Volume is the sum of the par value traded in the bond-year-month. Monthly Turnover is the ratio of Monthly Trading Volume to the total face value in the bond-year-month. Monthly Standard Deviation of Price denotes the standard deviation of quoted prices (per $100 par value) within the bond-year-month. $\mathbb{I}\{\text{Insured}\}$, $\mathbb{I}\{\text{Callable}\}$, and $\mathbb{I}\{\text{Sinkable}\}$ denote the insurance, callability, and sinkability status, respectively.

	1	2	3
Δ Fire	14.47***	-	-
	(3.006)	-	-
Δ Fire $\times$ $\mathbb{I}$(Year = 2005)	7.645**	12.88***	5.454*
	(3.123)	(3.041)	(3.130)
Δ Fire $\times$ $\mathbb{I}$(Year = 2007)	2.455	6.540**	1.902
	(3.209)	(3.219)	(3.327)
Δ Fire $\times$ $\mathbb{I}$(Year = 2008)	-5.949	-0.483	-1.267
	(7.536)	(9.894)	(9.111)
Δ Fire $\times$ $\mathbb{I}$(Year = 2009)	6.354	14.31	-5.699
	(8.266)	(10.71)	(13.88)
Δ Fire $\times$ $\mathbb{I}$(Year = 2010)	14.82***	22.74***	-3.036
	(5.634)	(8.081)	(10.28)
Δ Fire $\times$ $\mathbb{I}$(Year = 2011)	15.05***	24.60***	-4.394
	(4.068)	(6.572)	(9.425)
Δ Fire $\times$ $\mathbb{I}$(Year = 2012)	24.89***	39.72***	0.615
	(3.529)	(5.967)	(5.792)
Δ Fire $\times$ $\mathbb{I}$(Year = 2013)	16.11***	33.39***	-5.710
	(3.976)	(6.447)	(6.267)
Δ Fire $\times$ $\mathbb{I}$(Year = 2014)	19.08***	37.95***	3.380
	(4.294)	(7.280)	(5.827)
Δ Fire $\times$ $\mathbb{I}$(Year = 2015)	21.05***	45.52***	16.31**
	(4.476)	(8.192)	(6.328)
Δ Fire $\times$ $\mathbb{I}$(Year = 2016)	32.90***	59.90***	19.38***
	(5.045)	(9.039)	(6.969)
Δ Fire $\times$ $\mathbb{I}$(Year = 2017)	31.11***	60.07***	19.72***
	(5.099)	(9.361)	(6.848)
Δ Fire $\times$ $\mathbb{I}$(Year = 2018)	30.51***	64.20***	20.94***
	(4.848)	(9.575)	(6.728)
Δ Fire $\times$ $\mathbb{I}$(Year = 2019)	46.03***	86.65***	28.64***
	(6.549)	(10.97)	(6.866)
Δ Fire $\times$ $\mathbb{I}$(Year = 2020)	48.75***	91.65***	29.24***
	(7.563)	(11.84)	(6.931)
R^2	0.525	0.642	0.758
Δ Fire	26.73***	-	-
	(3.098)	-	-
Δ Fire $\times$ $\mathbb{I}$(Year >= 2015)	25.85***	32.60***	22.75***
	(6.211)	(4.735)	(4.478)
R^2	0.523	0.638	0.757
District-by-Trade-Year-Month Fixed Effects	Y	Y	Y
District-by-Maturity-Calendar-Date-Group Fixed Effects	N	Y	Y
Controls	N	N	Y
Observations	362,909	362,094	361,321

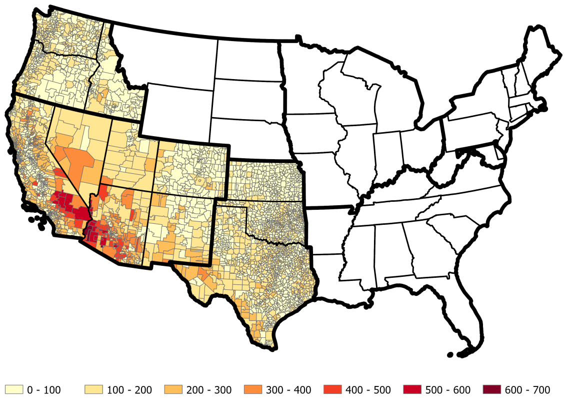
Table 2: Effect of Wildfire Risk Increases on Municipal Credit Spreads

This table reports the year-by-year and post-2014 impact of wildfire risk increases on municipal spreads, as described by Equation 6 and Equation 7. Standard errors are reported in parentheses, clustered at the county level. *, **, and *** indicate the corresponding p-value less than 0.10, 0.05, and 0.01, respectively. The credit spread of a bond is defined as the difference between its yield to maturity and its maturity-matched Municipal Market Analytics (MMA) yield benchmarks in basis points. Maturity calendar dates are grouped into intervals of 5 years (e.g., Santa Barbara Unified School District bonds maturing in 2040-44), and fire potentials are interpolated using a stepwise function from the historic level (1995-2004) to the mid-century prediction (2045-2054). We define ΔFire as the difference between the maturity-calendar-date-group-matched interpolated value and the historic level, which is standardized to a mean of zero and standard deviation of one. The regression includes the bond's district-by-maturity-calendar-date-group fixed effects and district-by-trade-year-month fixed effects. Controls include bond's log of the number of years before the maturity date and its insurance status interacted with the trade year indicator, the number of years since issuance, its monthly trading volume divided by its face value, its monthly standard deviation of prices, as well as its callability and sinkability status.

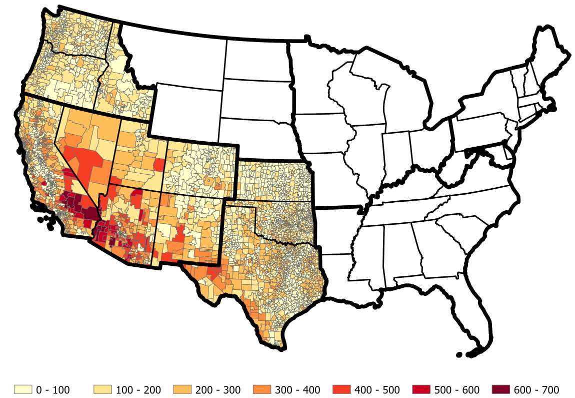
	1	2	3
Δ FIRE $\times$ $\mathbb{I}$(YEAR >= 2015)	22.746***	18.144***	18.699***
	(4.478)	(4.621)	(4.729)
Δ FIRE $\times$ $\mathbb{I}$(YEAR >= 2015) $\times$ $\mathbb{I}$(LOCALLY DEPENDENT)	-	11.195**	-
	-	(5.681)	-
Δ FIRE $\times$ $\mathbb{I}$(YEAR >= 2015) $\times$ $\mathbb{I}$(WITH A RACIAL MINORITY POPULATION)	-	-	11.495**
	-	-	(4.533)
Δ FIRE $\times$ $\mathbb{I}$(YEAR >= 2015) $\times$ $\mathbb{I}$(HIGH INCOME)	-	-	-0.533
	-	-	(5.379)
R^2	0.757	0.757	0.757
District-by-Trade-Year-Month Fixed Effects	Y	Y	Y
District-by-Maturity-Calendar-Date-Group Fixed Effects	Y	Y	Y
Controls	Y	Y	Y
Observations	361,321	361,321	361,321

Table 3: Effect of Wildfire Risk Increases on Municipal Credit Spreads - Heterogeneity

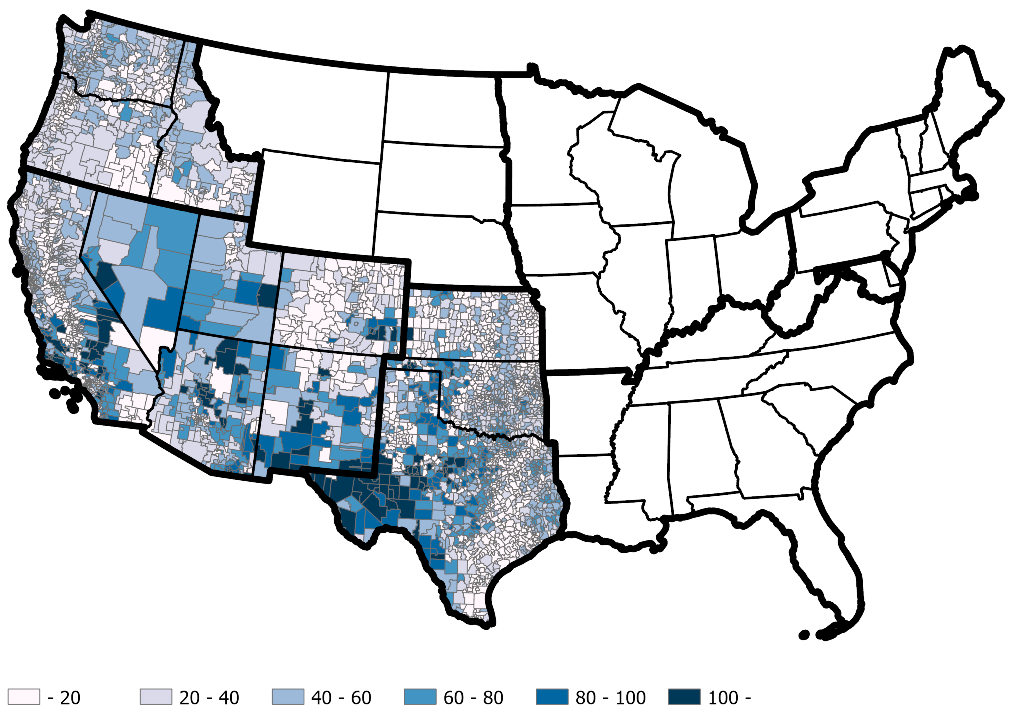
This table reports the heterogeneous impacts of wildfire risk increases on municipal spreads post-2014, as outlined in Equation 7 in which fire risk changes are further interacted with the indicator for heterogeneity. Standard errors are reported in parentheses, clustered at the county level. *, **, and *** indicate the corresponding p-value less than 0.10, 0.05, and 0.01, respectively. The nationwide average ratio of local to total school district revenue from 2005 through 2021 is about 40%. We classify school districts as "Locally Dependent" if their average revenues from local sources exceed 40% of total revenues. The White alone population decreased from 70% to 60% from 2010 to 2020 Census. We categorize school districts as "With a Racial Minority Population" if the proportion of White-alone population is below 65%. The nationwide average median household income by school district from 2005-2009 to 2017-2021 is $58,107 (in 2017 USD). We classify school districts as "High Income" if their own average median household income is above $58,107 (in 2017 USD). The credit spread of a bond is defined as the difference between its yield to maturity and its maturity-matched Municipal Market Analytics (MMA) yield benchmarks in basis points. Maturity calendar dates are grouped into intervals of 5 years (e.g., Santa Barbara Unified School District bonds maturing in 2040-44), and fire potentials are interpolated using a stepwise function from the historic level (1995-2004) to the mid-century prediction (2045-2054). We define ΔFIRE as the difference between the maturity-calendar-date-group-matched interpolated value and the historic level, which is standardized to a mean of zero and standard deviation of one. The regression includes the bond's district-by-maturity-calendar-date-group fixed effects and district-by-trade-year-month fixed effects. Controls include bond's logarithm of the number of years before the maturity date and its insurance status interacted with the trade year indicator, the number of years since issuance, its monthly trading volume divided by its face value, its monthly standard deviation of prices, as well as its callability and sinkability status.



(a) Historic weighted KBDI (1995-2004)



(b) Mid-century weighted KBDI (2045-2054)



(c) Difference

Figure 1: Wildfire Exposure by School District

This figure maps each school district's historic and mid-century weighted Keetch-Byram Drought Index (KBDI) based on equation 5, along with their difference in the Northwestern (NW), Southwestern (SW), and Southern Great Plains (SGP) regions, as classified by USGCRP (2017). The weights are determined by the number of housing units at the US census block level, further interacted with the Wildland-Urban Interface (WUI) classification. We restrict the sample to these regions because their average daily unweighted KBDI values exceed 400 in September, October, and November during the historic period from 1995 to 2004 (Brown et al., 2021). This threshold generally indicates late summer or early fall weather conditions with a high potential for wildfire events (Liu et al., 2010).

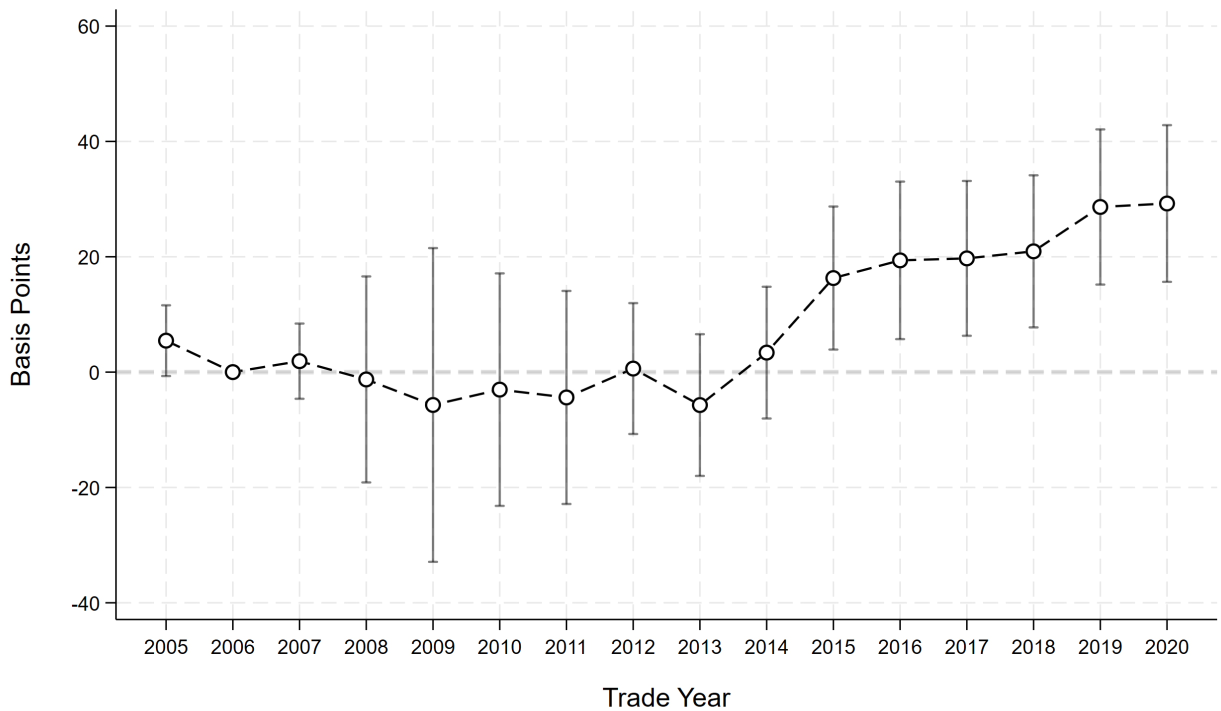


Figure 2: Effect of Wildfire Risk Increases on Municipal Credit Spreads

This figure plots the year-by-year impact of wildfire risk increases on the credit spreads of school district bonds, as described by Equation 6, with the baseline year set to 2006. The vertical lines denote the 95% confidence intervals, with standard errors clustered at the county level. The credit spread of a bond is defined as the difference between its yield to maturity, calculated from the monthly mean of its fundamental daily prices, and its maturity-matched Municipal Market Analytics (MMA) yield benchmarks in basis points, based on the last trade date each year-month. Maturity calendar dates are grouped into intervals of 5 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-35), and wildfire potentials are interpolated using a stepwise function from the historic level (1995-2004) to the mid-century prediction (2045-2054). We define ΔFire as the difference between the maturity-calendar-date-group-matched interpolated value and the historic level, which is standardized to a mean of zero and standard deviation of one. The regression includes the bond's district-by-maturity-calendar-date-group fixed effects and district-by-trade-year-month fixed effects. It also contains the log of the number of years before the maturity date and insurance status interacted with the trade year indicator. In addition, we control for the bond's age in years, its monthly trading volume divided by its face value, the monthly standard deviation of its prices, as well as its callability and sinkability status.

Online Appendix for

Pricing Climate Risks: Evidence from Wildfires and Municipal Bonds

A Two alternative measures of economic wildfire risk

Kearns et al. (2022) apply the First Street Wildfire Model (FS-WFM) to compute the property-level likelihood of wildfire occurrences for 2022 and 2052 using the moderate-emissions scenario (RCP 4.5). This data is available to academics for noncommercial use, although the highest resolution is at the census tract-level. Moreover, this dataset contains the total number of properties and the count of properties expected to be exposed to a likelihood of wildfire being x percent within the next 30 years relative to the baseline of 2023, where x denotes risk categories ranging from 0% to 36% or greater. Each category is defined as follows: 0%, 1%, 1-3%, 3-6%, 6-9%, 9-14%, 14-19%, 19-26%, 26-36%, and 36%+.

We do not use this measure in our analysis for two reasons. First, since it normalizes fire risk to zero before 2023, it is not possible to assign near-term risks for bonds maturing prior to 2023. Second, their most detailed predictions for non-commercial use are only available at the census tract level, which, in certain cases, overlaps more than one school district. Therefore, it is not possible to disaggregate risk measures while accounting for detailed variations in the distribution of the Wildland-Urban Interface (WUI).

Nonetheless, to assess the correlation between the weighted KBDI in our analysis and other peer-reviewed future wildfire risk measures, we disaggregate their data to the school district level using area weights. First, we overlay the census tract map with the US school district map to compute the area of each district that intersects with the tract. Second, we disaggregate the total number of properties and the count of properties expected to be exposed to wildfire based on the proportion of the overlaid area relative to the tract. Lastly, we sum up each quantity within the district and calculate the proportion of properties exposed to wildfire in each risk category.

Argonne National Laboratory calculates the Fire Weather Index (FWI) — developed by the Canadian Forest Service — across the contiguous US at a spatial resolution of 12 km for historic (1995-2004) and mid-century (2045-2054) periods (ANL, 2023). To generate the ensemble mean of the seasonal average daily FWI, they use Argonne's downscaled 12 km climate data under the high-emissions scenario (RCP 8.5) and across three climate models: Community Climate System Model (CCSM), Geophysical Fluid Dynamics Laboratory (GFDL), and Hadley Centre Global Environmental Model (HadGEM). It uses daily readings of temperature, relative humidity, wind speed, and 24-hour precipitation to assess fire potential, focusing on early to mid-afternoon conditions when weather conditions are favorable for fire spread.

As a robustness check, we use their summer average daily FWI to measure the fire potential of each school district, as the index reaches its peak during this season.[13] Given the consistency in spatial resolution, prediction time scale, and emissions scenario between KBDI and FWI, we apply the same method outlined in Section 2 to compute the weighted summer FWI.

Figure A2 maps the spatial distribution of the weighted KBDI, the weighted summer FWI, and the proportion of properties exposed to wildfire risks exceeding 14% — categorized as "severe" by Kearns et al. (2022) — across school districts in the contiguous United States. In the mid-century, the Northwest (NW), Southwest (SW), and Southern Great Plains (SGP) regions exhibit elevated wildfire potentials across all three metrics. The Northern Great Plains (NGP) show high fire risks for both FWI and the First Street Wildfire Model (FS-WFM), while the Southeast (SE) region displays high risks specifically for KBDI. In the final sample of the NW, SW, and SGP regions, the correlation between the change in KBDI from historic to mid-century and the FS-WFM index is 0.59. This correlation increases to 0.70 when considering the change in summer FWI from historic to mid-century.

[FIGURE A2 HERE]

[13] ANL (2023) divides the seasons into winter (December, January, February), spring (March, April, May), summer (June, July, August), and autumn (September, October, November).

B Name matching

In our economic wildfire risk data, we compute the weighted KBDI using the NCES school district boundary map, in which each district is uniquely identified by Local Education Agency Identification (LEAID) and the associated district names used in the Common Core of Data (CCD). But in our bond characteristics data, each district is uniquely identified by the 6-digit Committee on Uniform Securities Identification Procedures (CUSIP) and the associated issuer names. To the best of our knowledge, there is no established mapping between LEAID and the 6-digit CUSIP that can be used to assign climate risks to each bond issuer. Here, we describe the algorithm that we develop to match the 2010 vintage LEAID with the 6-digit CUSIP.

1. Within each state, drop duplicates and select unique string values for district and issuer names, along with their corresponding LEAID and 6-digit CUSIP, from the economic wildfire risk and bond characteristics data, respectively.

2. Within each state, extract the first word from each school district name and then apply the following filters:

    (a) Drop any cases where the first word extracted appears more than once, as we want to keep only unique names.

    (b) Keep only those cases where the length of the first word exceeds 3 characters to avoid generic names such as "San".

    (c) Exclude any cases where the first word includes directional terms, such as, North, Northern, Northeast, Northeastern, Northwest, Northwestern, South, Southern, Southeast, Southeastern, Southwest, Southwestern, East, Eastern, West, and Western.

3. Within each state, find issuer names that contain the filtered first words of school district names using a Cartesian product between two datasets, and apply the following filters:

    (a) Drop cases where multiple issuers are matched to a single school district.

    (b) Drop cases where multiple first words are matched to a single issuer.

After completing the algorithm-based matching, there may still be unmatched instances. In such cases, we manually match them according to the following guidelines:

1. Find special proper nouns within each issuer name and search for matches in district names.
2. If the previous step does not work, follow these steps:
   (a) Search for the issuer name on the Electronic Municipal Market Access (EMMA) and open its official statement.
   (b) Identify the issuer's special proper name from this document and match it.
   (c) Extract any relevant information from the description in the document.
   (d) Visit the NCES Search for Public School Districts.[14] Enter the information identified above and match accordingly.
3. Check the manually matched outcomes and categorize any unmatched cases as follows:
   (a) Multiple districts per issuance (e.g., AUBURN CALIF UN SCH DIST)
   (b) No official statement (e.g., BAY AREA SCH FOR INDPT STUDY INC CALIF)
   (c) No issuer name on EMMA (e.g., ARKANSAS ST DEV FIN AUTH CAP IMPT REV)
   (d) College (e.g., ALABAMA ST UNIV CTFS PARTN)
   (e) State, county, or city (e.g., PELHAM ALA)
   (f) Technical/vocational (e.g., EAST VY ARIZ INST OF TECHNOLOGY DIST NO 401)
   (g) Charter (e.g., CALIFORNIA MUN FIN AUTH CHARTER SCH LEASE REV)
   (h) Others (e.g., ARIZONA INDL DEV AUTH REV)
4. Drop the unmatched cases.

[14] https://nces.ed.gov/ccd/districtsearch/

C Suggestive evidence on housing value capitalization

The National Center for Education Statistics (NCES) Education Demographic and Geographic Estimates (EDGE) program uses the US Census Bureau's American Community Survey (ACS) to summarize data on economic and housing conditions for each school district. The estimates are derived from the ACS 5-year data, thus only accessible for the years from 2005-09 to 2017-21. For our analysis, we restrict our sample to the years from 2009 to 2021. We collect information on the median value of owner-occupied housing units, along with control variables such as mean household income and the unemployment rate. We then construct a balanced panel by merging this dataset together with our risk map using the Local Education Agency Identity (LEAID). Appendix Table A8 provides summary statistics.

If residents are forward-looking, they will consider anticipated wildfire risk changes when purchasing properties. The capitalization of future wildfire risk changes into housing values could potentially undermine school districts' ability to pay debt, alerting lenders to credit risks related to climate-driven wildfire events. To examine the association between future wildfire risk changes and housing values, we consider the following regression specification:

$$Y_{d,c,t} = \lambda_{c,t} + \alpha_d + \sum_{\substack{y=2009 \\ y\neq 2011}}^{2021} \beta_y \Delta \text{F}\textsc{ire}_d \mathbb{I}(\text{Y}\textsc{ear} = y) + \boldsymbol{\gamma}'\mathbf{X}_{d,t} + \varepsilon_{d,c,t}, \tag{8}$$

for school district d within county c and in year t. The outcome variable we consider is the median value of owner-occupied housing units.[15] We exclude school districts that span across more than one county to control for time-varying economic conditions at the county level ($\lambda_{c,t}$). Additionally, we exclude all observations starting from the year in which they were first impacted by large-scale wildfires, to isolate the effects of future fire risk changes from the direct impacts of historical wildfires. To align with the results from bond pricing, we restrict our sample to school districts located in the Northwest, Southwest, and Southern Great Plains regions.

[15] While the ACS housing value data are reported by respondents, recent evidence indicates that Census- and transactions-based price data analyses yield comparable results in other settings (Cassidy et al., 2022).

We define ΔFire by the difference between mid-century and historic weighted KBDI values within a district, standardized to a mean of zero and standard deviation of one. The covariates in $\mathbf{X}$ include the mean household income and unemployment rate to account for time-varying local economic conditions within a district. We include district fixed effects α_d to absorb any time-invariant differences across school districts. Moreover, we include county-by-year fixed effects $\lambda_{c,t}$ to control for time-varying local economic conditions at the county level. While we would like the coefficient of interest β_y to measure the year-to-year within-county variation in Y in response to a one standard deviation rise in future fire risks across districts, we here cannot include the rich set of district-by-year fixed effects that would account for economic conditions varying at the district level over time. If, for example, there are differential trends within school districts facing higher or lower future wildfire risk increases, these differing time trends could threaten the identification of the association between wildfire risk changes and housing values. We therefore consider the estimates as suggestive. Standard errors are clustered at the county level to account for within-county interdependence.

Figure A3 plots the year-by-year association of future wildfire risk changes with median value of owner-occupied housing units, which exhibits a persistent negative correlation since 2017. A one standard-deviation in the weighted KBDI is associated with an approximately \$6,000 (in 2017 USD) decrease in the median value of owner-occupied housing units in 2021 relative to 2011, which is equivalent to 2.3% of the average median value of owner-occupied housing units across all school districts. We also run a before-and-after analysis for the year 2015, similar to the equation (7). The corresponding coefficients have the same sign as the year-by-year estimates and are statistically significant at the 5% level.

Region	State
Northeast	Connecticut, Maine, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont, West Virginia
Southeast	Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Virginia
Midwest	Michigan, Minnesota, Missouri, Illinois, Indiana, Iowa, Ohio, Wisconsin
Northern Great Plains	Montana, Nebraska, North Dakota, South Dakota, Wyoming
Southern Great Plains	Kansas, Oklahoma, Texas
Northwest	Idaho, Oregon, Washington
Southwest	Arizona, California, Colorado, Nevada, New Mexico, Utah

Table A1: National Climate Assessment Regions of the Contiguous United States

Source: US Global Change Research Program (USGCRP, 2017)

Panel A: By State

	Number of Trades	Percent
Arizona	30,319	7.46
California	200,481	49.30
Colorado	10,313	2.54
Idaho	2,006	0.49
Kansas	7,767	1.91
New Mexico	3,488	0.86
Oklahoma	2,767	0.68
Oregon	6,413	1.58
Texas	105,135	25.85
Utah	6,313	1.55
Washington	31,645	7.78
Total	406,647	100.00

Panel B: By Trade Year

	Number of Trades	Percent
2005	8,556	2.10
2006	12,353	3.04
2007	13,533	3.33
2008	14,586	3.59
2009	15,622	3.84
2010	15,994	3.93
2011	16,650	4.09
2012	15,821	3.89
2013	20,893	5.14
2014	18,414	4.53
2015	22,378	5.50
2016	28,907	7.11
2017	39,239	9.65
2018	52,614	12.94
2019	53,948	13.27
2020	57,139	14.05
Total	406,647	100.00

Table A2: Sample Composition

	1	2	3	4
Δ Fire × $\mathbb{I}$(Year = 2005)	5.454*	2.756	3.125	-1.768
	(3.130)	(10.63)	(3.514)	(8.699)
Δ Fire × $\mathbb{I}$(Year = 2007)	1.902	9.415	0.984	5.010
	(3.327)	(8.626)	(3.711)	(6.734)
Δ Fire × $\mathbb{I}$(Year = 2008)	-1.267	-0.621	-3.238	-6.818
	(9.111)	(11.36)	(7.613)	(9.136)
Δ Fire × $\mathbb{I}$(Year = 2009)	-5.699	-11.18	-8.577	-18.26*
	(13.88)	(14.32)	(8.355)	(9.628)
Δ Fire × $\mathbb{I}$(Year = 2010)	-3.036	-2.867	-4.434	-5.111
	(10.28)	(12.56)	(7.859)	(8.941)
Δ Fire × $\mathbb{I}$(Year = 2011)	-4.394	1.618	-6.736	-7.182
	(9.425)	(10.34)	(7.675)	(9.779)
Δ Fire × $\mathbb{I}$(Year = 2012)	0.615	13.69	-0.912	5.820
	(5.792)	(11.42)	(6.803)	(9.007)
Δ Fire × $\mathbb{I}$(Year = 2013)	-5.710	7.165	-5.115	3.289
	(6.267)	(12.83)	(7.002)	(9.384)
Δ Fire × $\mathbb{I}$(Year = 2014)	3.380	7.231	3.533	7.977
	(5.827)	(10.67)	(6.403)	(8.687)
Δ Fire × $\mathbb{I}$(Year = 2015)	16.31**	23.68**	15.94**	20.77**
	(6.328)	(10.05)	(6.610)	(8.749)
Δ Fire × $\mathbb{I}$(Year = 2016)	19.38***	28.93**	18.74***	26.74***
	(6.969)	(11.60)	(6.841)	(8.731)
Δ Fire × $\mathbb{I}$(Year = 2017)	19.72***	29.42***	19.62***	29.66***
	(6.848)	(11.33)	(7.065)	(8.850)
Δ Fire × $\mathbb{I}$(Year = 2018)	20.94***	30.60***	20.65***	32.51***
	(6.728)	(11.62)	(6.986)	(9.295)
Δ Fire × $\mathbb{I}$(Year = 2019)	28.64***	40.38***	28.54***	42.05***
	(6.866)	(11.20)	(7.183)	(9.003)
Δ Fire × $\mathbb{I}$(Year = 2020)	29.24***	45.30***	29.18***	45.21***
	(6.931)	(11.45)	(7.261)	(9.518)
R^2	0.758	0.712	0.751	0.701
Δ Fire × $\mathbb{I}$(Year >= 2015)	22.75***	23.62***	22.86***	25.19***
	(4.478)	(4.205)	(2.675)	(2.877)
R^2	0.757	0.712	0.751	0.701
Equal Weights	N	Y	N	Y
More Than One District Per County	Y	Y	N	N
Cluster for Standard Error	County	County	District	District
Number of Bonds	52,280	52,280	68,780	68,780
Number of Districts	1,641	1,641	2,458	2,458
Observations	361,321	361,321	469,511	469,511

Table A3: Wildfire Wildfire Risk Increases and Municipal Spreads - Robustness Specification

This table reports the year-by-year and post-2014 impact of wildfire risk increases on municipal credit spreads. Standard errors are reported in parentheses. *, **, and *** indicate the corresponding p-value less than 0.10, 0.05, and 0.01, respectively. The credit spread of a bond is defined as the difference between its yield to maturity and its maturity-matched Municipal Market Analytics (MMA) yield benchmarks in basis points. Maturity calendar dates are grouped into intervals of 5 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-35), and fire potentials are interpolated using a stepwise function from the historic level (1995-2004) to the mid-century prediction (2045-2054). We define ΔFire as the difference between the maturity-calendar-date-group-matched interpolated value and the historic level, which is standardized to a mean of zero and standard deviation of one. The regression includes the bond's district-by-maturity-calendar-date-group fixed effects and district-by-trade-year-month fixed effects. Controls include bond's logarithm of the number of years before the maturity date and its insurance status interacted with the trade year indicator, the number of years since issuance, its monthly trading volume divided by its face value, its monthly standard deviation of prices, as well as its callability and sinkability status. Column (1) presents the benchmark specification. Column (2) weights each observation by the inverse of the count of distinct bonds within each state for a specific trade year. Column (3) additionally includes bonds issued in counties that contain only one district or span across two counties. Column (4) removes geographic restrictions and applies equal weighting across states.

	1	2	3
Δ Fire	10.20***	-	-
	(2.366)	-	-
Δ Fire × $\mathbb{I}$(Year = 2005)	8.036***	10.23***	2.147
	(2.497)	(2.589)	(2.877)
Δ Fire × $\mathbb{I}$(Year = 2007)	3.186	5.331**	1.612
	(2.425)	(2.363)	(2.108)
Δ Fire × $\mathbb{I}$(Year = 2008)	-5.595	-2.841	-2.617
	(6.400)	(8.367)	(7.541)
Δ Fire × $\mathbb{I}$(Year = 2009)	4.109	9.392	-7.080
	(7.299)	(9.175)	(11.30)
Δ Fire × $\mathbb{I}$(Year = 2010)	12.32**	17.11**	-5.405
	(4.866)	(6.778)	(8.701)
Δ Fire × $\mathbb{I}$(Year = 2011)	12.49***	18.14***	-7.357
	(3.396)	(5.737)	(8.247)
Δ Fire × $\mathbb{I}$(Year = 2012)	23.82***	33.11***	-4.109
	(3.571)	(5.107)	(4.917)
Δ Fire × $\mathbb{I}$(Year = 2013)	15.14***	27.24***	-7.434
	(3.065)	(5.713)	(4.703)
Δ Fire × $\mathbb{I}$(Year = 2014)	17.03***	31.24***	0.580
	(3.145)	(6.555)	(4.429)
Δ Fire × $\mathbb{I}$(Year = 2015)	19.72***	37.62***	12.36***
	(3.507)	(7.264)	(4.639)
Δ Fire × $\mathbb{I}$(Year = 2016)	31.19***	51.04***	15.55***
	(4.345)	(8.231)	(5.053)
Δ Fire × $\mathbb{I}$(Year = 2017)	29.18***	50.99***	15.08***
	(4.325)	(8.446)	(5.030)
Δ Fire × $\mathbb{I}$(Year = 2018)	28.60***	54.43***	16.41***
	(4.056)	(8.695)	(4.959)
Δ Fire × $\mathbb{I}$(Year = 2019)	42.27***	74.29***	23.20***
	(5.628)	(10.01)	(5.115)
Δ Fire × $\mathbb{I}$(Year = 2020)	44.73***	78.84***	23.47***
	(6.501)	(10.79)	(5.338)
R^2	0.553	0.665	0.768
Δ Fire	21.22***	-	-
	(2.646)	-	-
Δ Fire × $\mathbb{I}$(Year >= 2015)	24.28***	28.49***	20.49***
	(5.293)	(4.073)	(3.968)
R^2	0.551	0.662	0.768
District-by-Trade-Year-Month Fixed Effects	Y	Y	Y
District-by-Maturity-Calendar-Date-Group Fixed Effects	N	Y	Y
Controls	N	N	Y
Observations	642,516	639,950	638,378

Table A4: Wildfire Risk Increases and Municipal Spreads - Contiguous United States

This table reports the year-by-year and post-2014 impact of wildfire risk increases on municipal credit spreads. The sample includes the contiguous United States, with 116,649 bonds issued by 5,177 school districts. Standard errors are reported in parentheses, clustered at the county level. *, **, and *** indicate the corresponding p-value less than 0.10, 0.05, and 0.01, respectively. The credit spread of a bond is defined as the difference between its yield to maturity and its maturity-matched Municipal Market Analytics (MMA) yield benchmarks in basis points. Maturity calendar dates are grouped into intervals of 5 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-35), and fire potentials are interpolated using a stepwise function from the historic level (1995-2004) to the mid-century prediction (2045-2054). We define ΔFire as the difference between the maturity-calendar-date-group-matched interpolated value and the historic level, which is standardized to a mean of zero and standard deviation of one. The regression includes the bond's district-by-maturity-calendar-date-group fixed effects and district-by-trade-year-month fixed effects. Controls include bond's logarithm of the number of years before the maturity date and its insurance status interacted with the trade year indicator, the number of years since issuance, its monthly trading volume divided by its face value, its monthly standard deviation of prices, as well as its callability and sinkability status.

	1	2	3
Δ Fire	17.07***	-	-
	(4.861)	-	-
Δ Fire × $\mathbb{I}$(Year = 2005)	7.011	13.41**	0.763
	(5.789)	(6.451)	(5.517)
Δ Fire × $\mathbb{I}$(Year = 2007)	0.847	6.735	1.954
	(4.073)	(5.738)	(6.010)
Δ Fire × $\mathbb{I}$(Year = 2008)	-2.442	1.736	4.257
	(7.486)	(10.53)	(8.283)
Δ Fire × $\mathbb{I}$(Year = 2009)	11.35	19.24	-3.297
	(10.98)	(13.98)	(16.99)
Δ Fire × $\mathbb{I}$(Year = 2010)	22.61***	31.13***	0.730
	(7.401)	(9.694)	(11.87)
Δ Fire × $\mathbb{I}$(Year = 2011)	19.06***	31.57***	-3.590
	(5.582)	(9.144)	(12.15)
Δ Fire × $\mathbb{I}$(Year = 2012)	23.10***	48.42***	0.504
	(6.563)	(5.731)	(7.917)
Δ Fire × $\mathbb{I}$(Year = 2013)	7.792	45.22***	-2.838
	(7.399)	(6.272)	(8.705)
Δ Fire × $\mathbb{I}$(Year = 2014)	9.104	50.64***	6.490
	(6.369)	(6.451)	(8.233)
Δ Fire × $\mathbb{I}$(Year = 2015)	16.42***	56.54***	17.16**
	(5.985)	(6.779)	(8.669)
Δ Fire × $\mathbb{I}$(Year = 2016)	27.49***	71.82***	21.49**
	(5.690)	(7.276)	(9.432)
Δ Fire × $\mathbb{I}$(Year = 2017)	24.02***	71.81***	21.02**
	(5.714)	(7.072)	(8.809)
Δ Fire × $\mathbb{I}$(Year = 2018)	22.18***	75.88***	22.21**
	(5.498)	(7.375)	(8.824)
Δ Fire × $\mathbb{I}$(Year = 2019)	38.26***	98.11***	30.47***
	(6.336)	(8.059)	(8.932)
Δ Fire × $\mathbb{I}$(Year = 2020)	44.66***	105.1***	33.15***
	(6.455)	(8.472)	(8.770)
R^2	0.505	0.641	0.758
Δ Fire	28.00***	-	-
	(5.867)	-	-
Δ Fire × $\mathbb{I}$(Year >= 2015)	20.65***	31.50***	21.37***
	(5.950)	(3.532)	(2.877)
R^2	0.503	0.637	0.757
District-by-Trade-Year-Month Fixed Effects	Y	Y	Y
District-by-Maturity-Calendar-Date-Group Fixed Effects	N	Y	Y
Controls	N	N	Y
Observations	362,909	362,098	361,325

Table A5: Wildfire Risk Increases and Municipal Spreads - Summer Fire Weather Index

This table reports the year-by-year and post-2014 impact of wildfire risk increases on municipal credit spreads. The weighted Fire Weather Index is used. Standard errors are reported in parentheses, clustered at the county level. *, **, and *** indicate the corresponding p-value less than 0.10, 0.05, and 0.01, respectively. The credit spread of a bond is defined as the difference between its yield to maturity and its maturity-matched Municipal Market Analytics (MMA) yield benchmarks in basis points. Maturity calendar dates are grouped into intervals of 5 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-35), and fire potentials are interpolated using a stepwise function from the historic level (1995-2004) to the mid-century prediction (2045-2054). We define ΔFire as the difference between the maturity-calendar-date-group-matched interpolated value and the historic level, which is standardized to a mean of zero and standard deviation of one. The regression includes the bond's district-by-maturity-year-group fixed effects and district-by-trade-year-month fixed effects. Controls include bond's logarithm of the number of years before the maturity date and its insurance status interacted with the trade year indicator, the number of years since issuance, its monthly trading volume divided by its face value, its monthly standard deviation of prices, as well as its callability and sinkability status.

	1	2	3
Δ Fire	12.66***	-	-
	(2.809)	-	-
Δ Fire × $\mathbb{I}$(Year = 2005)	7.659***	12.98***	5.162*
	(2.900)	(2.607)	(3.062)
Δ Fire × $\mathbb{I}$(Year = 2007)	1.709	5.137*	3.225
	(2.873)	(3.088)	(3.117)
Δ Fire × $\mathbb{I}$(Year = 2008)	-7.032	-2.649	0.818
	(9.495)	(11.61)	(10.64)
Δ Fire × $\mathbb{I}$(Year = 2009)	4.820	11.36	0.203
	(8.813)	(10.22)	(12.24)
Δ Fire × $\mathbb{I}$(Year = 2010)	11.37*	18.94**	1.376
	(6.035)	(8.324)	(10.00)
Δ Fire × $\mathbb{I}$(Year = 2011)	9.878***	19.44***	0.389
	(3.455)	(6.288)	(9.114)
Δ Fire × $\mathbb{I}$(Year = 2012)	20.25***	31.06***	0.169
	(4.554)	(6.791)	(7.171)
Δ Fire × $\mathbb{I}$(Year = 2013)	16.22***	26.15***	-3.602
	(3.825)	(7.218)	(7.619)
Δ Fire × $\mathbb{I}$(Year = 2014)	21.54***	29.75***	3.832
	(4.176)	(7.455)	(6.849)
Δ Fire × $\mathbb{I}$(Year = 2015)	20.70***	36.63***	16.31**
	(4.362)	(9.140)	(6.792)
Δ Fire × $\mathbb{I}$(Year = 2016)	31.52***	51.93***	19.64***
	(5.877)	(11.15)	(7.262)
Δ Fire × $\mathbb{I}$(Year = 2017)	30.08***	52.11***	20.02***
	(5.917)	(11.88)	(7.620)
Δ Fire × $\mathbb{I}$(Year = 2018)	29.24***	56.17***	20.58***
	(5.471)	(11.97)	(7.334)
Δ Fire × $\mathbb{I}$(Year = 2019)	44.19***	77.38***	27.45***
	(7.588)	(13.91)	(7.676)
Δ Fire × $\mathbb{I}$(Year = 2020)	50.01***	83.99***	28.81***
	(7.727)	(14.55)	(7.928)
R^2	0.530	0.646	0.760
Δ Fire	22.65***	-	-
	(3.288)	-	-
Δ Fire × $\mathbb{I}$(Year >= 2015)	27.13***	30.80***	20.70***
	(7.054)	(7.001)	(5.824)
R^2	0.527	0.642	0.760
District-by-Trade-Year-Month Fixed Effects	Y	Y	Y
District-by-Maturity-Calendar-Date-Group Fixed Effects	N	Y	Y
Controls	N	N	Y
Observations	291,588	290,882	290,203

Table A6: Wildfire Risk Increases and Municipal Spreads - Excluding Directly-affected Districts

This table reports the year-by-year and post-2014 impact of wildfire risk increases on municipal spreads, excluding transactions from school districts affected by large-scale wildfire events since their first occurrence. Standard errors are reported in parentheses, clustered at the county level. *, **, and *** indicate the corresponding p-value less than 0.10, 0.05, and 0.01, respectively. The credit spread of a bond is defined as the difference between its yield to maturity and its maturity-matched Municipal Market Analytics (MMA) yield benchmarks in basis points. Maturity calendar dates are grouped into intervals of 5 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-35), and fire potentials are interpolated using a stepwise function from the historic level (1995-2004) to the mid-century prediction (2045-2054). We define ΔFire as the difference between the maturity-calendar-date-group-matched interpolated value and the historic level, which is standardized to a mean of zero and standard deviation of one. The regression includes the bond's district-by-maturity-calendar-date-group fixed effects and district-by-trade-year-month fixed effects. Controls include bond's logarithm of the number of years before the maturity date and its insurance status interacted with the trade year indicator, the number of years since issuance, its monthly trading volume divided by its face value, its monthly standard deviation of prices, as well as its callability and sinkability status.

	1	2	3
Δ Fire $\times$ $\mathbb{I}$(Year = 2005)	5.454*	5.904	1.072
	(3.130)	(4.304)	(2.753)
Δ Fire $\times$ $\mathbb{I}$(Year = 2007)	1.902	6.675*	7.151***
	(3.327)	(3.901)	(2.355)
Δ Fire $\times$ $\mathbb{I}$(Year = 2008)	-1.267	2.083	6.378
	(9.111)	(10.00)	(6.108)
Δ Fire $\times$ $\mathbb{I}$(Year = 2009)	-5.699	2.433	11.20*
	(13.88)	(13.57)	(5.980)
Δ Fire $\times$ $\mathbb{I}$(Year = 2010)	-3.036	0.476	11.50*
	(10.28)	(12.05)	(6.117)
Δ Fire $\times$ $\mathbb{I}$(Year = 2011)	-4.394	-4.551	9.187
	(9.425)	(11.15)	(5.689)
Δ Fire $\times$ $\mathbb{I}$(Year = 2012)	0.615	-0.0721	8.272
	(5.792)	(7.592)	(5.247)
Δ Fire $\times$ $\mathbb{I}$(Year = 2013)	-5.710	-6.104	3.463
	(6.267)	(7.854)	(6.030)
Δ Fire $\times$ $\mathbb{I}$(Year = 2014)	3.380	1.903	9.841
	(5.827)	(7.601)	(6.151)
Δ Fire $\times$ $\mathbb{I}$(Year = 2015)	16.31**	15.92*	21.85***
	(6.328)	(8.153)	(6.520)
Δ Fire $\times$ $\mathbb{I}$(Year = 2016)	19.38***	18.86**	24.47***
	(6.969)	(8.875)	(6.901)
Δ Fire $\times$ $\mathbb{I}$(Year = 2017)	19.72***	18.25**	24.98***
	(6.848)	(8.993)	(7.185)
Δ Fire $\times$ $\mathbb{I}$(Year = 2018)	20.94***	18.84**	26.40***
	(6.728)	(8.898)	(6.988)
Δ Fire $\times$ $\mathbb{I}$(Year = 2019)	28.64***	25.63***	32.10***
	(6.866)	(8.973)	(7.106)
Δ Fire $\times$ $\mathbb{I}$(Year = 2020)	29.24***	27.20***	34.55***
	(6.931)	(9.288)	(7.668)
R^2	0.758	0.773	0.750
Δ Fire $\times$ $\mathbb{I}$(Year >= 2015)	22.75***	20.77***	19.00***
	(4.478)	(5.333)	(4.047)
R^2	0.757	0.772	0.750
Stepsize (years)	5	2	8
District-by-Trade-Year-Month Fixed Effects	Y	Y	Y
District-by-Maturity-Calendar-Date-Group Fixed Effects	Y	Y	Y
Controls	Y	Y	Y
Observations	361,321	360,046	361,672

Table A7: Wildfire Wildfire Risk Increases and Municipal Spreads - Step Size for Interpolation

This table reports the year-by-year and post-2014 impact of wildfire risk increases on municipal credit spreads. Standard errors are reported in parentheses. *, **, and *** indicate the corresponding p-value less than 0.10, 0.05, and 0.01, respectively. The credit spread of a bond is defined as the difference between its yield to maturity and its maturity-matched Municipal Market Analytics (MMA) yield benchmarks in basis points. Maturity calendar dates are grouped into intervals of 5 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-35), and fire potentials are interpolated using a stepwise function from the historic level (1995-2004) to the mid-century prediction (2045-2054). We define ΔFire as the difference between the maturity-calendar-date-group-matched interpolated value and the historic level, which is standardized to a mean of zero and standard deviation of one. The regression includes the bond's district-by-maturity-calendar-date-group fixed effects and district-by-trade-year-month fixed effects. Controls include bond's logarithm of the number of years before the maturity date and its insurance status interacted with the trade year indicator, the number of years since issuance, its monthly trading volume divided by its face value, its monthly standard deviation of prices, as well as its callability and sinkability status. Column (1) presents the benchmark specification. Columns (2) and (3) use step sizes of 2 and 8 years, respectively, for interpolating wildfire risks.

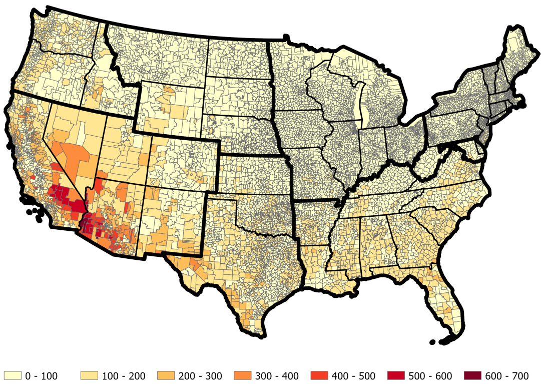
	Mean	Standard Deviation
Fire Risk Change	28.91	28.90
Median value of owner-occupied housing units in 2017 USD (in thousands of dollars)	260.01	224.57
Mean household income in 2017 USD (in thousands of dollars)	74.88	28.74
Unemployment rate (%)	4.93	2.43

Table A8: Summary Statistics for Socioeconomic and Municipal Finance Data

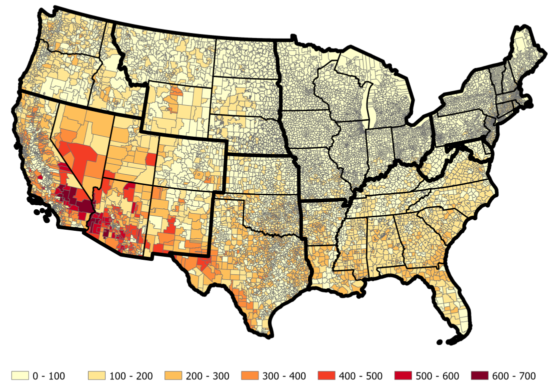
This table reports the summary statistics for the variables used in the sample. The sample comprises 18,066 district-year observations spanning from 2009 to 2021, with 1,887 school districts.

Figure A1: Distribution of Time to Maturity by Trade Year

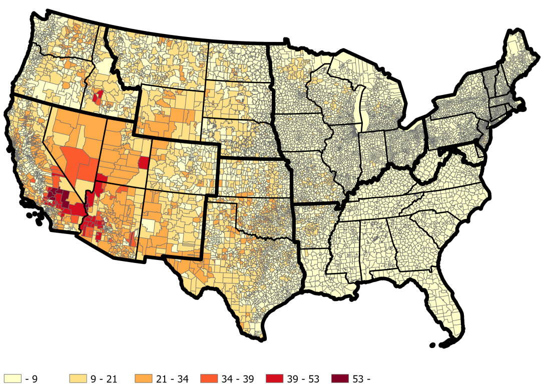
This figure displays the distribution of time-to-maturity in years for the bonds traded each year.



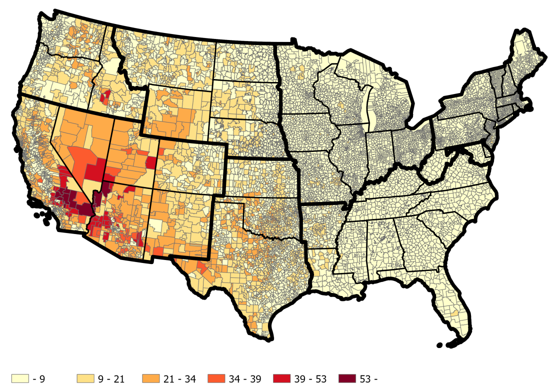
(a) Historic weighted KBDI (1995-2004)



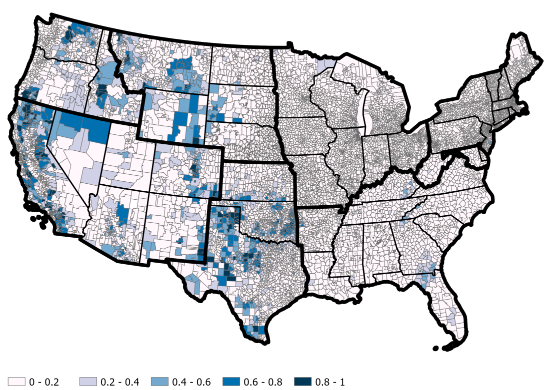
(b) Mid-century weighted KBDI (2045-2054)



(c) Historic weighted FWI (1995-2004)



(d) Mid-century weighted FWI (2045-2054)



(e) Percent of properties with a fire risk > 14%

Figure A2: Alternative Measures of Wildfire Risks

This figure maps each school district's KBDI, FWI, and the proportion of properties exposed to fire risks exceeding 14% over the next 30 years relative to 2023, calculated from Brown et al. (2021), ANL (2023), and Kearns et al. (2022), respectively. KBDI values exceeding 400 and FWI values exceeding 21 indicate late summer or early fall weather conditions associated with an elevated risk of wildfire occurrences (Liu et al., 2010; ANL, 2023).

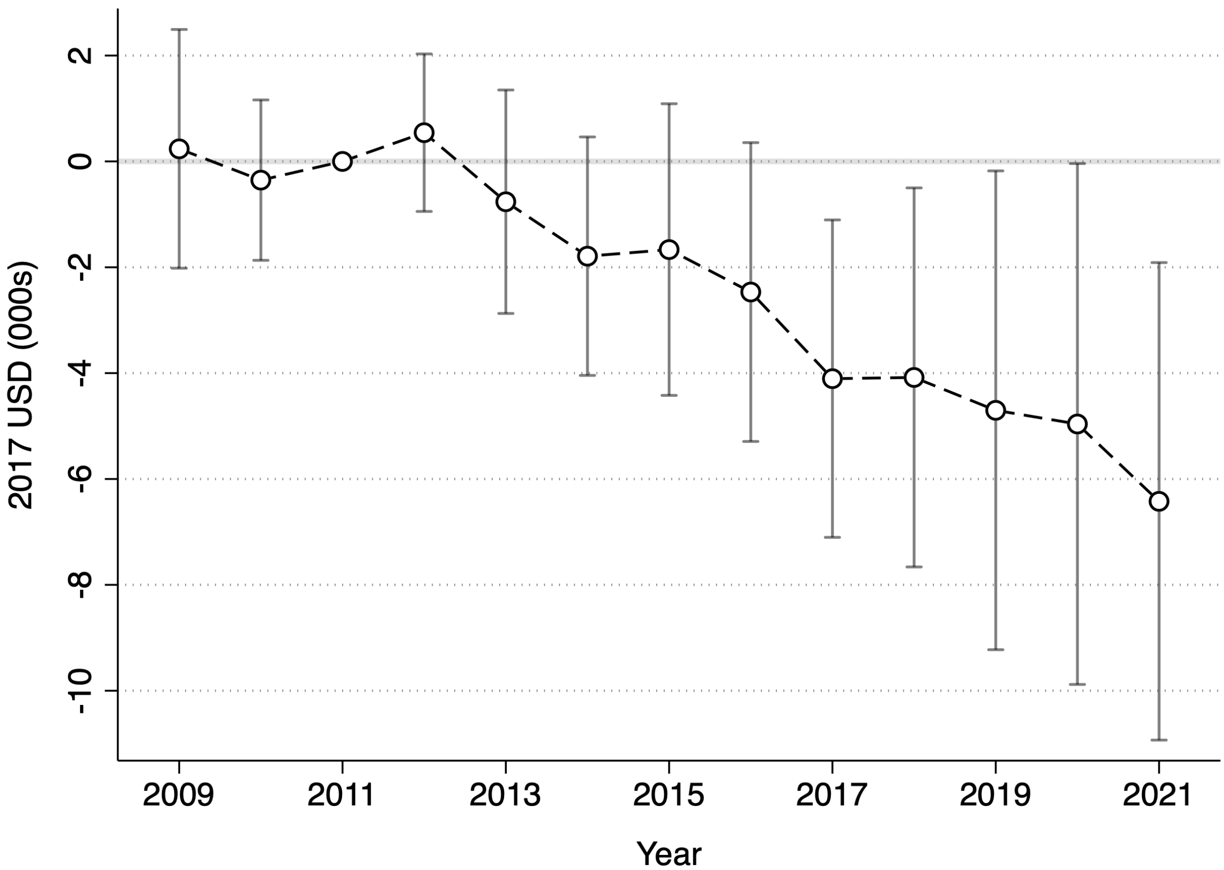


Figure A3: Association between Future Wildfire Risk Increases and Housing Values

This figure plots the year-by-year impacts of wildfire risk increases on the median value of owner-occupied housing units, as described by Equation 8, with the baseline period set to 2011. The vertical lines represent the 95% confidence intervals, with standard errors clustered at the county level. We exclude all observations starting from the year in which they were first impacted by large-scale wildfires. We define ΔFIRE as the difference between mid-century and historic weighted KBDI values per district. The regression includes district fixed effects and county-by-year fixed effects. Additionally, we control for the mean household income and unemployment rate of each district.