Pricing Climate Risks:

Evidence from Wildfires and Municipal Bonds*

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Abstract

How are public finances affected by climate-driven wildfire risk changes? Using high-resolution meteorological forecasts, land use data, and US municipal bond spreads, we find that municipalities facing greater future wildfire exposure already incur higher borrowing costs: A one standard deviation increase in future wildfire risk is associated with a 7 (8) basis point rise in primary (secondary) market spreads - over 15% of the sample mean. Impacts appear larger in areas with higher minority populations and greater reliance on local revenue. Our study contributes to the broader literature by introducing a new approach to evaluating the capitalization of evolving physical climate risks.

Keywords: Wildfires, Climate Risk, Municipal Bond, Fiscal Costs of Climate Change

JEL Classification Codes: G12, H74, Q54

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1 Introduction

Wildfires are imposing increasing costs on the US economy. Already in 2018, the direct costs of wildfires, 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). The indirect impacts from wildfire smoke have been estimated to include over 15,000 excess deaths per year (Qiu et al., 2025). More recently, the catastrophic January 2025 Southern California wildfires may turn out to be the costliest natural disaster in US history, with insured property losses alone estimated at $75 billion.[1] Furthermore, historical wildfire events have also been associated with substantial fiscal costs (Baylis and Boomhower, 2023; Liao and Kousky, 2022), and even some municipal debt defaults.[2] Even more concerning is that the potential for wildfires is expected to continue to rise in many parts of the US due to climate change (Brown et al., 2021).

Despite this growing evidence on their potential economic significance, wildfires have received relatively little attention in the literature on the financial and economic consequences of climate change. For example, wildfire impacts are typically not modeled in integrated climate-economic assessment frameworks and feature limited reflection in recent estimates of the social cost of carbon (see, e.g., EPA 2023). And while a growing literature has revealed the potential of *past* wildfire events to affect a range of economic outcomes, the consequences of climate-induced *future* wildfire risk changes remain comparatively understudied. In this paper, we fill this research gap by providing novel evidence that expected future wildfire risk changes are already associated with significant financial and economic effects, specifically higher borrowing costs for vulnerable US municipalities. To the best of our knowledge, this is also the first quantification of the capitalization of future wildfire risks in financial markets.[3]

[1] "Economic impact of the Los Angeles wildfires," UCLA Anderson Forecast https://www.anderson.ucla.edu/about/centers/ucla-anderson-forecast/economic-impact-los-angeles-wildfires. Accessed on 2025-03-19.

[2] "Audited Financial Statements and Supplemental Information," Town of Paradise https://www.townofparadise.com/sites/default/files/fileattachments/finance/page/2861/town_of_paradise_afs_2023.pdf. Accessed on 2025-04-24.

[3] We are aware of one industry report which considers the association between municipal bond prices and a proprietary forward-looking risk score ("risQ") that includes wildfires in a random forest analysis (NYSE: ICE, 2022). They argue that

The specifics of our analysis can be summarized as follows. The main outcome of interest is municipal bond spreads, defined by the difference between a bond's yield-to-maturity and a maturity-matched risk-free benchmark yield.[4] One of the important differences between wildfires and other climatic risks that have been studied in recent literature, such as exposure to long-run sea-level rise (e.g., Bernstein et al. 2019; Goldsmith-Pinkham et al. 2023), is that wildfire risks are already present and changing in the near and medium run, but differentially so across locations. In addition, the same municipality usually issues multiple bonds of different maturities at the same time. We leverage these variations to construct bond-specific measures of climate risk that varies across bonds issued *within the same municipality*. Our risk measure combines bond maturity structure with estimates of local historical and future physical wildfire potentials and the number of housing units in the Wildland Urban Interface (where vegetation meets residential structures) to quantify the local economic wildfire risk change embodied over the lifetime of each bond. Importantly, this research design permits the inclusion of a rich set of control variables including county-by-month fixed effects (e.g., Santa Barbara County in May 2024) and district-by-maturity-date-group fixed effects (e.g., Montecito Union School District bonds maturing between 2040 and 2049). Despite these rich fixed effects, variation in future wildfire risk is ultimately observational. We therefore note that our estimated impacts are associations.

Our central finding is that anticipated future wildfire risk increases are already associated with substantial effects on the borrowing costs of US municipalities. We specifically estimate that a one standard deviation increase in future wildfire exposure is associated with a 7 (8)-basis point increase in school district primary (secondary) market bond spreads post-2014, which is equivalent to over 15% of the mean spreads in the sample. The estimated impacts are robust to other estimation methods and the exclusion of communities directly

future climate risks are *not* capitalized into US bond prices. This difference in results could be due to their pooling across years (2006-2021) or other methodological differences, but is difficult to assess due to limited details in the report.

[4] Our main analysis focuses on school district bonds due to their fine-scaled spatial variation in climatic risks, close link to local property markets, and overall economic significance, with an estimated debt outstanding of $450 billion in 2022 (Ciccarone, 2023). This focus also aligns with recent literature (e.g., Goldsmith-Pinkham et al. 2023). For robustness, we also present the pricing of future fire risks in county-level general obligation bonds in Table A19.

affected by wildfire events over our sample period. We also consider potential confounders including future population changes, future heat risks, and longer-term wildfire risk changes beyond each bond's maturity. In our heterogeneity analyses, we find that the effects of wildfire risks on public bond yields are larger in districts with larger non-white population shares. In the primary market, we also observe 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.[5] A similar pricing pattern is observed for county general obligation bonds. We find that the capitalization of future fire risks is attenuated under a moderate emissions scenario and dominated by the Western United States. Overall, however, our results suggest that anticipated future wildfire risk changes are already associated with significant changes in financial markets, municipal borrowing costs, and vulnerable communities.

Reassuringly, these quantitative results align with qualitative evidence that municipal bond market participants are increasingly concerned about rising wildfire risk. For example, both S&P Global and market data provider ICE have recently produced estimates of municipalities' future wildfire risk exposure for investors.[6,7] A recent textual analysis of official municipal bond statements also found that more than 10% of general revenue bonds mention climate change explicitly (Bolstad et al., 2020). More broadly, influential investment entities such as BlackRock have highlighted the potential risks posed by future warming to municipal bond markets.[8] These qualitative signals are consistent with the interpretation that investors are increasingly attuned to expected future wildfire risks and their potential impacts on municipal public finance. At the same time, the interpretation of our results is also subject to important caveats. Future wildfire risk changes are associated with climatic

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

[6] "Quantifying the climate physical risk facing US muni bonds," S&P Global https://www.spglobal.com/sustainable1/en/insights/blogs/quantifying-the-climate-physical-risk-facing-us-muni-bonds. Accessed on 2026-05-04.

[7] "Pricing wildfires into municipal bonds," ICE https://www.ice.com/insights/fixed-income-data/pricing-wildfire-risk-into-municipal-bonds. Accessed on 2026-05-04.

[8] "Investors Underappreciate Climate-Related Risks in Their Portfolios," BlackRock https://www.blackrock.com/corporate/newsroom/press-releases/article/corporate-one/press-releases/investors-underappreciate-climate-related-risks-in-their-portfolios. Accessed on 2026-05-04.

risks - such as heat and precipitation - that may affect counties through other channels as well, such as crop yields. While we show results controlling for heat risk, our use of climate-driven variation in wildfire risk changes means that we ultimately cannot control separately for all climatic variables that affect wildfire risk.

Finally, to interpret the economic magnitude of our estimates, we develop and calibrate a simple discrete-time structural model of municipal credit risk. The exercise is in the spirit of the calibration of Goldsmith-Pinkham et al. (2023), who use a Merton (1974) model to map yield premia from sea-level rise into changes in local-government cash flows. Our model features random local revenue growth, debt rollover, partial default, and risk-neutral investors. We find that the estimated fire-risk spread can be rationalized as either (1) a 14 basis point decline in average annual revenue growth, (2) a 2 percentage point increase in the probability of poor revenue growth, or (3) a proportional 3% increase in annual revenue growth volatility. As we discuss in subsection 3.4, these implied damages seem plausible, although somewhat conservative, when compared with related estimates from the literature.[9]

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, 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). This literature shows that information frictions can contribute disproportionately to limited climate risk capitalization for housing as an asset class (where one buyer with incorrect beliefs may be the marginal (pricing) agent as in Bakkensen and Barrage

[9]For example, Meier et al. (2023) find that, in southern Europe, a one standard deviation increase in a region's summer Fire Weather Index for forested areas is associated with a roughly 1 percentage point decrease in local GDP per capita growth over the following year. This is larger than our growth-damage estimate of 14 basis points, although the numbers are not directly comparable, as we are looking at the *revenue* effects of *future* Fire Weather Index increases.

2022), and that owner-occupied buyers command smaller climate risk discounts compared to investor-buyers (e.g., Bernstein et al. 2019; Hino and Burke 2021). For financial assets, one may thus expect stronger climate risk capitalization, ceteris paribus. Empirically, certain future climate risks have been shown to be capitalized at least partly into equity markets (e.g., drought trends as in Hong et al. 2019), corporate bonds markets (e.g., sea level rise as in Allman 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).[10] Our contributions to this specific literature are twofold: To the best of our knowledge, this paper is the first to (1) demonstrate the capitalization of anticipated climate-driven future wildfire risk changes into asset prices, and (2) utilize our research design with *bond-specific* climate risk measures that differ within municipalities. That is, in contrast to prior literature considering cross-sectional variation in long-run climatic risks (e.g., Painter 2020), we leverage near- and medium-run changes in wildfire risks to evaluate the effects of climatic risks *within* municipalities across bonds and time. As other climatic risks are also already changing significantly and differentially so across space (e.g., extreme precipitation, Marvel et al., 2023; Kim et al., 2023), we believe that our approach has broader applicability outside the study of wildfire risks as well.

Second, this analysis adds to a nascent body of work demonstrating the capitalization of *current* wildfire risks into asset prices, which to date include property insurance premiums (Boomhower et al., 2024), housing (as discussed below), options (Ouazad, 2022), city bonds (Berry-Stölzle and Hao, 2026), and mortgage-backed securities (Kahn et al., 2024).[11] Several recent studies have also used broad measures of historic natural disaster exposure that may

[10]Several studies have documented associations between *general* climate risk indices from proprietary sources and bond prices, such as (Smull et al., 2023)'s cross-sectional analysis of US municipal bond prices and a proprietary climate risk index and several analyses of sovereign borrowing costs and a broad climate risk and resilience index (Beirne et al., 2021; Cevik and Jalles, 2022). Some recent studies, such as Mallucci (2022) and Phan and Schwartzman (2024), have also used quantitative models to simulate the impacts of changing climate risks on sovereign bond markets.

[11]Macro-fiscal risks from declining insurance quality, imperfect risk pricing, and partial mortgage risk pass-through to government-sponsored enterprises has also been documented for hurricanes Sastry et al. (2026).

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).[12] In addition, Lopez et al. (2025) find a positive association between historic wildfire smoke pollution and borrowing costs in the healthcare sector, as well as distributional impacts on high-minority areas. 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, 2026), employment and income (Borgschulte et al., 2022; Walls and Wibbenmeyer, 2023; Roth Tran and Wilson, 2023), local business activities (Addoum et al., 2025), crop yields (Behrer and Wang, 2024), student test scores (Wen and Burke, 2022), and outdoor recreational activities (Gellman et al., 2025), in addition to well-established adverse health impacts (Wen et al., 2023; Qiu et al., 2025). 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., 2025). 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), historic wildfire events (McCoy and Walsh, 2018), and exposure to smoke plumes (Huang and Skidmore, 2024; Addoum et al., 2024).

A fourth related strand is the emerging literature examining the fiscal perils associated with climate-related disasters (see Barrage 2025 for a recent review). Most relevant, Liao and Kousky (2022) find that wildfire events increase the probability of municipal budget deficits by 25 percentage points. Similarly, Jerch et al. (2023) document adverse impacts of

[12]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).

hurricane strikes on several US municipal fiscal outcomes and 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,[13] 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 fire suppression costs (Wibbenmeyer et al., 2019; Plantinga et al., 2022; Baylis and Boomhower, 2023) and Medicare spending (Miller et al., 2017). But none of them explores the rising borrowing costs that may arise due to growing wildfire risks. 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 or lead to further unintended consequences, such as hindered human capital accumulation (Park et al., 2020; Biasi et al., 2025).

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.

2 Data

2.1 Bond trades in the secondary and primary markets

We use the Refinitiv Data Platform (RDP) Application Programming Interface (API) 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." We also use this dataset as the main source for the primary market

[13]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).

analysis as it contains the issue price of each bond. Our secondary market transaction data comes 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.

First, we construct a monthly panel of yield-to-maturity in the secondary market using historical trade data at the bond level. 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 provided 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. We then compute the trading volume and price standard deviation of a bond for each year-month.

In the secondary market for municipal bonds, 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).

Second, we create a yield-to-maturity dataset in the primary market using bond-level issue prices. As in the secondary market analysis, we address clerical errors by excluding issues without issue prices or par values, those priced above $150 or below $50 per $100 par value, and those with coupon rates exceeding 20%. We also remove issues with a time-to-maturity of less than 365 days and more than 30 years. We then compute the yield to maturity and match it with maturity-matched MMA municipal yield benchmarks based on the issue date to calculate credit spreads. Table 1 summarizes the changes in sample size from this process.

We then merge these two transaction datasets with the economic 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 A.

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 also provide a robustness check on our main regression by including bonds issued in school districts that span across two counties. Lastly, we conduct a robustness check to investigate whether the pricing of wildfire risk changes in school district bonds extends to other general obligation municipal bonds such as county bonds. See Appendix B for further details on the county bond data extraction from the Bloomberg Terminal.

2.2 Economic wildfire risks

2.2.1 Future wildfire potential

From an economic perspective, wildfire risk includes two factors: meteorological conditions indicative of wildfire events 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, Park et al. (2023) adopt the Canadian Forest Fire Weather Index (FWI) to compute fire potential across the globe, which covers a historical estimate (2000-2014) that includes our first maturity year, as well as scenario-based future projections (2015-2050) that include our last maturity year at a spatial resolution of 25 km. The FWI is a widely-used metric for assessing meteorological conditions related to wildfire events using factors such as temperature, humidity, wind speed, and precipitation (van Wagner, 1987). Our FWI projection data are based on weather predictions from 33 Earth System Models (ESMs) in the Coupled Model Inter-comparison Project Phase 6 (CMIP6) under four different Shared Socioeconomic Pathways (SSPs). We focus on the high-emissions (SSP5-8.5) scenario as a benchmark to align with market expectations in the midpoint of our sample period (2001-2021).[14] We also show results from a heterogeneity analysis which assumes that market participants during our sample period expected more ambitious climate policy as in the SSP2-4.5 scenario. In order to isolate climate signals from noisy inter-annual fluctuations, we average the FWI over ten-year intervals within each model

[14]To quantify the effect of expected future wildfire risk changes on municipal bond prices, the relevant climate scenario is the one that matches market participants' *expectations* at the time of a given trade. In 2014, the IPCC explicitly labeled RCP 8.5 as a "Baseline" scenario and showed that, without additional policy efforts, warming was expected to be in a range overlapping with RCP 8.5. In more recent years, technological and policy changes have shifted this outlook (Hausfather and Peters, 2020). New IPCC estimates published after the end of our sample period project baseline long-run warming levels of 3.2°C (median), between RCP 4.5 and 8.5 scenarios (IPCC, 2022).

(e.g., $2000 - 2009, 2010 - 2019, \cdots, 2040 - 2049$), similar to Qiu et al. (2025).[15] We use an ensemble mean by averaging the FWI across 33 ESMs.

The US Global Change Research Program divides the contiguous United States into seven regions to evaluate region-specific climate risks in its National Climate Assessment (NCA): Northwest (NW), Southwest (SW), Northern Great Plains (NGP), Southern Great Plains (SGP), Midwest (MW), Northeast (NE), and Southeast (SE) (USGCRP, 2017).[16] We restrict our benchmark sample to regions that have historically experienced meaningful potential for wildfire events, specifically the NW, SW, and SGP regions.[17] This choice is in line with the broader literature on fiscal climate risks, which commonly restricts its samples to areas where a given risk is sufficiently relevant so as to form a more suitable comparison group.[18] To count the number of housing units exposed to different FWI levels, we overlay 25 km resolution FWI 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.

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 (NLCD) 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 FWI assessment. For example, a census block in downtown San Francisco may exhibit a high level of FWI by mid-century. However, accounting for its WUI status could reduce its fire potential significantly, as there is little

[15] Predicting inter-annual weather variations is, in general, subject to substantial uncertainty, particularly when weather indices are downscaled to granular spatial scales.

[16] See Table A2 for the grouping of states by region.

[17] Liu et al. (2010) define a Keetch-Byram Drought Index (KBDI) value greater than 400 as indicative of a high wildfire potential. Based on the simulated KBDI from Brown et al. (2021), the NW, SW, and SGP regions exhibit high meteorological potential for fire.

[18] For example, Deryugina (2017) and Jerch et al. (2023) focuses on Eastern (Atlantic + Gulf) U.S. areas with hurricane exposure, Goldsmith-Pinkham et al. (2023) focus on coastal states, and Liao and Kousky (2022) focus their attention on California municipalities that experienced a sufficiently large fire at some point.

flammable vegetation.

To evaluate the fire risk of each bond issuer, we aggregate the FWI 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 FWI for each interval, using the number of housing units in the wildland-urban interface areas as weights: for $p \in \{2000-2009, 2010-2019, \cdots, 2040-2049\}$,

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

Figure 1 maps the weighted FWI of school districts for the 2000-2009 period, along with their changes over time. In general, the Southwestern region exhibits high risk levels. But the Southern Great Plains and Northern Great Plains area additionally stand out when considering the changes over time.[19]

[Figure 1 Here]

2.2.2 Historic wildfire perimeters

This paper studies how fire risk changes are priced in the municipal bond market. But throughout our sample period, a number of fires occurred across the US. Indeed, Liao and Kousky (2022) document that, in California, the probability of municipal budget deficits increases in the aftermath of wildfires. Moreover, there is burgeoning evidence on the direct costs of historic fire 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,

[19] Brown et al. (2021) computes the Keetch-Byram Drought Index (KBDI) across the contiguous United States at a spatial resolution of 12 km, but only for historic (1995-2004) and mid-century (2045-2054) periods. They 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. We only use the FWI for our analysis because it provides a continuous time series from 2000 to 2050 and it is derived from the latest CMIP6 weather projections.

we exclude observations that were directly affected by such events in our robustness checks.

To identify school districts affected by large-scale fires, we use the Monitoring Trends in Burn Severity (MTBS) data 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 each year y at the school district levels as follows:

$$D_{d,y} = \frac{1}{\sum_{j=1}^{N_d} \mathrm{HU}_j} \times \sum_{i=1}^{N_d} \Big[\mathrm{HU}_i \times \mathbb{I}(i \text{ is in the MTBS fire footprint in year } y) \Big]. \quad (2)$$

We use $D_{d,y}$ to filter large-scale wildfire events that occurred after 2005 to match municipal bond transaction data. We define 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 75,389 bond-month observations in the secondary market and 23,314 issues in the primary market.

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 wildfire potential over forested regions in the Southwestern and Northwestern US since 1982 as well. Both findings 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 range from 2006 to 2051 in our secondary market data and from 2002 to 2052 in our primary market data, respectively. To leverage the variation in wildfire 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 10 years. For a bond b issued by a district d, let $m(b)$ denote the group to which its maturity calendar date belongs:

$$m(b) = \begin{cases} 0 & \text{if its maturity calendar date is before 2010,} \\ 1 & \text{if its maturity calendar date falls between 2010 and 2020,} \\ \dots & \\ 4 & \text{if its maturity calendar date is after 2040.} \end{cases} \tag{3}$$

We define the maturity-calendar-date-group-matched fire risk change as the difference between the maturity-calendar-date-group-matched value and the historical level (2000-2009):

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

Importantly, $\Delta\text{Fire}_{d,m(b)}$ is linked to the predetermined maturity calendar dates on which the principal is expected to be paid off and, consequently, this value remains constant (time-invariant) across all transaction dates for a given bond.

Figure 2 visualizes observed variation in economic wildfire risk across bonds, districts, and time. Three points relevant to our study design emerge. First, the same school district usually issues multiple bonds of different maturities at the same time. For example, in July 2005, Sonoma Valley Unified school district issued bonds with maturities ranging from 1-14 years. This provides variation in bonds' wildfire risk *within* a school district-issue date. Second, the same school district also has multiple bond issuance dates. This provides variation in the wildfire risk of bonds with a given maturity length (e.g., 10 years) and in the pricing of bonds with a given maturity date group (e.g., maturing in 2030-39) *within* a school district. Third, within a county, there is variation in wildfire risk increases both for bonds issued on the same date and with the same maturity length and maturity date. For example, 10-year bonds issued in June 2021 in Sonoma County differ substantially in their associated wildfire risk increase.

[Figure 2 Here]

Table 1 summarizes the sample construction and provides summary statistics.

[Table 1 Here]

In the secondary market, after winsorizing at the 1% level, the spreads range from -61.16 to 279.62 basis points. The average time to maturity is 7.73 years, and the weighted FWI is 4.47. The sample comprises 393,573 bond-month trades spanning from 2005 to 2020, with 50,457 bonds issued by 1,475 school districts. Conditional on trading, the mean (median) number of bonds traded in a county-by-trade-year-month is 17.54 (6).

On the other hand, in the primary market, after winsorizing at the 1% level, the spreads vary from -53.04 to 145.24 basis points. The average time to maturity is 10.29 years, and the average weighted FWI is 4.96. The sample comprises 147,711 issues spanning from 2001 to 2021 by 1,854 school districts. Conditional on issuance, the mean (median) number of bonds issued in a district-issue-year-month is 18.67 (15). The mean (median) number of bonds traded is higher in the primary market because issuers structure debt with multiple maturities — either level or escalating — when borrowing large amounts of capital upfront.

Appendix Table A5 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 year.

2.4 Socioeconomic and municipal finance data

We collect socioeconomic and municipal finance data for school districts for heterogeneity analyses and robustness checks. First, our municipal finance data is from the National Center for Education Statistics (NCES) Common Core Data School District Finance survey, which provides the data on school district finances. We focus on revenues to determine whether districts with a greater reliance on property taxes incur higher interest rates in response to rising wildfire risks. In particular, we categorize school district revenues into three sources: (i) property tax revenues, (ii) other local revenue streams that include sales taxes, and (iii) unearmarked federal and state aids. In constructing these measures, we focus specifically on fungible funds within this data, which are not tied to specific programs and, thus, districts can use more flexibly to reduce fiscal shocks. Second, the NCES Education Demographic and Geographic Estimates (EDGE) program uses the Census Bureau's American Community Survey (ACS) to summarize socioeconomic data 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. Lastly, the Integrated Climate and Land Use Scenarios (ICLUS) project of the Environmental Protection Agency (EPA) produces population projections based on the Intergovernmental Panel on Climate Change scenarios at the metropolitan, micropolitan, and rural county levels. We collect population projections to ensure that our main results are not merely driven by changes in other tax bases rather than wildfire risk. We disaggregate the ICLUS population projections to the Census Block level and re-aggregate them to the school district level. We then merge these datasets with our bond data using the Local Education Agency Identification.

3 Empirical methods and results

3.1 Identification strategy

We use an identical empirical strategy to estimate the correlation between wildfire risk changes and municipal credit spreads in both primary and secondary markets, which only differ in their covariates. For expositional purposes, we explain the strategy only for the primary market. Specifically, we adopt the following regression equation:

$$\begin{aligned} \textsc{Spread}_{b,d,c,t} = & \sum_{\substack{y=2001 \\ y \neq 2005}}^{2021} \mathbb{I}(\textsc{Year} = y) \ \left[\beta_y \Delta\textsc{Fire}_{d,m(b)} + \boldsymbol{\theta}_y' \mathbf{Z}_{b,d,c,t}\right] \\ & + \lambda_{c,t} + \alpha_{d,m(b)} + \boldsymbol{\gamma}' \mathbf{X}_{b,d,c,t} + \varepsilon_{b,d,c,t}, \end{aligned} \tag{5}$$

for the issuance of bond b, by 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 issue date for that bond.[20] The principal is expected to be paid off on fixed future dates (e.g., Santa Barbara Unified School District bonds maturing in 2045) and we group such maturity calendar dates into 10-year intervals (e.g., Santa Barbara Unified School District bonds maturing between 2040-2049). To isolate climate signals from noisy inter-annual fluctuations on projected climate risks, the weighted FWIs are calculated for each decennial period similar to Qiu et al. (2025). We define ΔFire as the difference between the maturity calendar date group-matched future weighted FWI 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., 2023). Other covariates in $\mathbf{X}$ include the natural logarithm of each bond's face value, its sales method

[20] Painter (2020) considers not just yields at issuance but also annualized gross spreads to account for higher search costs when marketing bond issuances with higher climate risks. Since the RDP API does not provide gross spreads data, we focus on yield at issuance, making our estimate likely a lower bound on the capitalization of wildfire risks in the primary market.

(negotiated or competitive), its callability and sinkability status, as well as standardized revenues from local sources to capture district-wide time-varying economic conditions. In the secondary market analysis, we consider each bond's age in years, its monthly trading volume divided by its face value (turnover), the monthly standard deviation of its prices, its callability and sinkability status, as well as standardized revenues from local sources.

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. This specification effectively compares bonds maturing in the same decadal period issued by the same school district. For example, in Figure 2, this would be a comparison among all the bonds in the purple frame within Sonoma Valley Unified school district. These fixed effects are fully collinear with the level of wildfire risk changes. Therefore, the overall level effects cannot be identified in this specification. We can, however, estimate the change in the effect of the associated wildfire risk changes on bond spreads over time as we observe bonds with the same maturity-date-group issued by the same school district at multiple times as shown in Figure 2. Additionally, we include county-by-issue-year-month fixed effects $\lambda_{c,t}$ to control for any time-varying local economic conditions. While our research design allows us to include rich fixed effects, future fire risk increases are not random. Thus, our estimand should be interpreted as suggestive evidence rather than a tightly causal effect. 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.

The coefficient β_y measures the year-to-year variation in spreads in response to a one standard deviation increase in wildfire risk changes relative to 2005. To summarize impacts after 2014, we adopt the following specification:

$$\text{SPREAD}_{b,d,c,t} = \beta\ \mathbb{I}(\text{YEAR} \geq 2015)\Delta\text{FIRE}_{d,m(b)} + \sum_{\substack{y=2001 \\ y\neq 2005}}^{2021} \mathbb{I}(\text{YEAR} = y)\boldsymbol{\theta}'_y \mathbf{Z}_{b,d,c,t}$$
$$+ \lambda_{c,t} + \alpha_{d,m(b)} + \boldsymbol{\gamma}'\mathbf{X}_{b,d,c,t} + \varepsilon_{b,d,c,t}, \quad (6)$$

where the year indicators are replaced by $\mathbb{I}(\text{YEAR} \geq 2015)$, 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 5.

3.2 Primary market 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 the primary market. In column (1), our regression analysis adopts parsimonious controls by including county-by-issue-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 maturity dates within the same district. In column (3), our benchmark regression specification additionally controls for bond-level characteristics.

[TABLE 2 HERE]

In the most parsimonious specification, we find a positive correlation of 4.4 between future wildfire risk changes and spreads in the baseline period (transactions before 2014). This positive correlation can be partly attributed to the varying maturity dates of bonds issued by the same 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 factors, we see that the impact of future wildfire risk changes on spreads begins to diverge in the late 2010s. 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. (2023) find 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 2001 to 2013 becomes statistically indistinguishable from the baseline issue year. We find that the difference in spreads among bonds with varying maturities begins to widen further in the mid-2010s, which is consistent with recent findings on sea-level rise and heat risks by Goldsmith-Pinkham et al. (2023) and Acharya et al. (2022). On average, a one standard-deviation increase in the weighted FWI leads to a 7.1-basis point rise in school district bond spreads post-2014, which is about 21.2% of the average spreads in the sample. Figure 3 plots the year-by-year estimates in column (3), which suggest a marked increase in the capitalization of future wildfire risks into financial markets.

[Figure 3 Here]

3.3 Secondary market results

Although municipal bonds are relatively illiquid compared to other asset classes, they are also traded among investors in the secondary market after issuance. To identify the correlation between future wildfire risk changes and the market's assessment of school districts' creditworthiness, we use the same empirical strategy as in Equation 5 focusing on the fundamental price in the secondary market. Table 3 presents the year-by-year and post-2014 impacts of wildfire risk changes on the credit spreads of school district bonds in the secondary market.

[Table 3 Here]

In the most parsimonious specification (Column 1), we observe a positive correlation of 11.2 between future wildfire risk changes and spreads in the baseline period (transactions before 2014), which can be attributed to varying maturity dates. After controlling for district-by-maturity-calendar-date-group fixed effects in column (2), spreads begin to diverge in the late 2010s, potentially due to time-varying bond characteristics such as bond age or liquidity. After controlling for bond-level characteristics, the positive correlation diminishes, and the yearly variation in credit spreads from 2006 to 2014 becomes statistically insignificant relative to the baseline trade year. Similar to the primary market, we find positive and statistically significant yearly coefficients starting 2015. On average, a one standard-deviation increase in the weighted FWI leads to an 8.0-basis point rise in school district bond spreads post-2014, which is about 14.9% of the average spreads in the sample. Figure 4 visualizes the year-by-year estimates in column (3).

[Figure 4 Here]

3.4 Evaluation

Before proceeding, we provide a brief quantitative and qualitative evaluation of our results' plausibility. First, we note that, anecdotally, municipal bond market participants appear to be paying increasing attention to rising wildfire risks. For example, both S&P Global and market data provider ICE have recently produced estimates of municipalities' future wildfire risk exposure for investors.[21,22] As another example, after the January 2025 Los Angeles fires, many investment firms and ratings agencies published statements about potential impacts on municipal bond markets.[23] Finally, recent estimates also indicate that 4-10% of (large counties') municipal bonds' official statements mention climate change Bolstad et al. (2020).

In Appendix C, we develop and calibrate a simple model of municipal credit risk. In the spirit of the calibration exercise in Goldsmith-Pinkham et al. (2023), we use the model to translate our spread estimates into potential risks to municipal tax revenue. Time is discrete

[21] "Quantifying the climate physical risk facing US muni bonds," S&P Global https://www.spglobal.com/sustainable1/en/insights/blogs/quantifying-the-climate-physical-risk-facing-us-muni-bonds. Accessed on 2026-05-04

[22] "Pricing wildfires into municipal bonds," ICE https://www.ice.com/insights/fixed-income-data/pricing-wildfire-risk-into-municipal-bonds. Accessed on 2026-05-04.

[23] "California Wildfire Challenges May Test US Public Finance Resilience," Fitch Wire https://www.fitchratings.com/research/us-public-finance/california-wildfire-challenges-may-test-us-public-finance-resilience-14-01-2025. Accessed on 2026-05-04.
It should be noted that both the materiality and pricing implications of wildfire risks remain debated among market participants, highlighting the potential novelty of our findings vis-à-vis more observational comparisons.

in the model, tax revenues available for repaying debt follow a random growth process, and bonds are priced by risk-neutral lenders. The municipality can service debt with tax revenues or by rolling over into new bonds. Partial default occurs when debt obligations exceed the sum of tax revenues and the maximum possible rollover amount (which is determined endogenously by future credit risk). First, we calibrate the model to match the average secondary-market spread of 0.5%, as well as several other key features of municipal taxes and debt. Then we ask, which changes to the revenue process would be consistent with a spread increase of 8 basis points (our secondary-market empirical estimate)? We find that the estimated spread can be rationalized as either (1) a 14 basis point decline in average annual revenue growth, (2) a 2 percentage point increase in the probability of poor revenue growth over typical remaining time to maturity (7.7 years), or (3) a proportional 3% increase in annual revenue growth volatility. In the first two cases, the corresponding losses in revenue present value range from around 1.2% to 2.2%. See Appendix C for further details.

We are unaware of research that would provide a direct benchmark for our fiscal damage estimates, but the magnitudes seem plausible when compared with related research. Most closely-related, Meier et al. (2023) find that, in southern Europe, a one standard deviation increase in a region's summer FWI for forested areas is associated with a roughly 1 percentage point decrease in local GDP per capita growth over the following year. Goldsmith-Pinkham et al. (2023) report that a municipal bond premium of 5.3 basis points due to sea-level rise corresponds to a 1.3-8.1% present value cash-flow loss or a 0.8-4.2% proportional cash-flow volatility increase. Acharya et al. (2022) find that heat-stress damages of 1% of local GDP correspond to municipal spreads of around 25 basis points. And Colacito et al. (2019) show that state-level output growth declines by 0.15-0.25 percentage points in response to a 1°F rise in average summer temperature.

3.5 Robustness

The results so far indicate that bonds with larger increases in embodied future wildfire risk command economically and statistically significantly higher yields. We conduct several robustness checks on our benchmark regression for both primary and secondary markets by adopting different estimation methods, excluding communities directly impacted by wildfire events during our sample period, adding controls for longer-term wildfire risk changes beyond a bond's maturity, and including future heat risk changes and projected population growth rates in addition to wildfire risk. First, we assign weights to bond-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 A5). Column (4) in Table 2 and Table 3 report the year-by-year and post-2014 impacts using these weights. The post-2014 average impact of wildfire risk on spreads remains economically and statistically significant, and the year-by-year patterns are qualitatively similar.

Second, we expand our sample by including bonds issued in counties that contain either only one district or span across two counties to improve the representativeness of our sample. The number of districts increases from 1,854 to 2,938 in the primary market whereas the number of bonds and districts in the secondary market increases from 50,457 to 65,267 and 1,475 to 2,012, respectively. Accordingly, the sample size increases from 147,711 to 206,823 in the primary market and from 393,573 to 505,218 in the secondary market, respectively. The associated summary statistics are provided in Appendix Table A6, which are similar to those of our benchmark sample. With this expansion, school districts are not nested within counties, and thus, we cluster standard errors at the school district level. In addition, we employ county-year-month fixed effects for districts nested within a single county, while applying district-year-month fixed effects for those spanning multiple counties. Columns (5) and (6) in Table 2 and Table 3 present the year-by-year and post-2014 impacts after including these instances. The former does not use weights, while the latter does. The average impact post-2014 remain significant, and the year-by-year patterns remain qualitatively similar to those observed in the benchmark regression.

Third, we exclude observations starting from the year-month in which school districts were first affected by large-scale wildfire events to isolate the capitalization of future fire risks from the direct impact of historic wildfires. Appendix Table A7 and Table A8 replicate the main regression analysis using the sample without directly affected communities. The year-by-year estimates exhibit similar patterns.

Fourth, we explore the extent to which our estimated capitalization effects are driven by wildfire risk changes during each bond's time-to-maturity versus longer-term wildfire risk changes in each school district. We formally add controls for each school district's wildfire risk changes over either the +10 or +20 years *after* each bond's maturity date to the benchmark specification. The results are shown in Appendix Table A13 and Table A14. For the primary market, the results show that (i) the estimated effect of during-bond-lifetime wildfire risk increases is robust to controlling for longer-term risk changes, and (ii) the coefficients on the longer-term risk changes are generally imprecise or even negative in some cases. For the secondary market, the during-bond-lifetime wildfire risk effects remain similar in the +20 years beyond specification but are attenuated in the +10 years beyond specification. We conjecture that this latter attenuation may be due to roll-over risk which may be especially relevant for the secondary market in the closer aftermath of a bond's maturity date. Overall, however, these results are broadly consistent with the notion that our estimated effects are driven by wildfire risks directly relevant for each bond more so than general longer-term trends.

Fifth, we include changes in heat risks in addition to wildfire risks to see if our main result is driven by extreme heat events. Appendix Table A9 and Table A10 replicate our main regression analysis on the capitalization of wildfire risks using an extended Heat Index by Lu and Romps (2022), which incorporates both temperature and humidity to evaluate how hot it feels to the human body (see Appendix D for details on quantifying economic heat risk). It is worth noting that the FWI is in general negatively correlated with the Heat Index because the FWI is positively correlated with dry air, whereas the Heat Index increases with humidity.[24] The post-2014 average impacts of wildfire risk on spreads in primary and secondary markets are about 4.9 - 6.9 and 4.1 - 7.0 basis points when we control for the number of summer days with a seasonal average daily maximum heat index above 95 - 125 degrees.[25] The estimated impact attenuates when controlling for the seasonal average daily maximum Heat Index. This is because wildfire risk and these alternative heat measures are more positively correlated (see Appendix Figure A3).

Sixth, we include district-wide future population growth rates in addition to wildfire risk changes to account for other confounding factors affecting the future tax base. Specifically, from a theoretical perspective, if tax revenue growth fails to match the pace of population growth, it may result in fiscal strain and a deterioration in the quality of public services (Ladd, 1994). Put differently, both extremely low and high population growth in the future can impose a fiscal burden. Appendix Table A11 and Table A12 replicate our main regression analysis by categorizing projected population growth rates into four groups to capture the non-linear relationship between population dynamics and bond spreads. The categories $\mathbb{I}\{\textsc{Low}\}$, $\mathbb{I}\{\textsc{Moderate}\}$, $\mathbb{I}\{\textsc{High}\}$, and $\mathbb{I}\{\textsc{Very High}\}$ correspond to population growth rate in the maturity year within the intervals of $(-\infty, 0.005)$, $[0.005, 0.25)$, $[0.25, 0.4)$, and $[0.4, \infty)$, respectively. Towards the end of the 2010s, municipal bond spreads exhibit a U-shaped pattern with population growth rates. Spreads increase when growth rates are either extremely high or low, whereas they decline for municipalities with moderate growth rates. Even after accounting for population growth rates, our results on the pricing of wildfire risk changes in both the primary and secondary markets remain robust.

[24]Recent empirical studies highlight the importance of accounting for both temperature and humidity, showing that mortality impacts extend not only to the elderly but also to infants (Wilson et al., 2024).

[25]For further details, see "Heat Index Chart," National Oceanic And Atmospheric Administration National Weather Service https://www.noaa.gov/sites/default/files/2022-05/heatindex_chart_rh.pdf.

3.6 Heterogeneity and further analysis

We examine whether there exist any unequal impacts of wildfire risk changes on credit spreads. We first test whether credit spreads are higher for districts with a greater reliance on property tax revenues, as might be expected if the estimated impacts reflect risks to future property values (Auh et al., 2022; Goldsmith-Pinkham et al., 2023). Importantly, districts with a high share of income and sales taxes may have a greater capacity to absorb fiscal shocks from climate-driven property damages. Moreover, since US school districts have historically relied heavily on local property tax revenues, significant disparities in per pupil spending exist across districts within states. To mitigate such disparities, most states have changed their school finance systems using state-level funding to equalize resources across districts. Indeed, research shows that these reforms improve test scores (Lafortune et al., 2018) and intergenerational mobility (Biasi, 2023). Higher school quality protects property values and, consequently, reduces default risks from climate-related damages. To explore how school finance systems affect the pricing of climate risks, we first collect data on school district revenue sources: (i) property tax revenues, (ii) other local revenue sources, and (iii) both federal and state aids that are not earmarked for specific purposes. We then calculate the ratio of property tax revenues to the sum of these resources. A lower share indicates that a district may be more resilient to climate risks if it can rely more on other local revenues or intergovernmental aids. We interact this ratio with wildfire risk changes in Equation 6.

The first and second columns in Panel A of Table 4 report the post-2014 impact of wildfire risk changes on municipal spreads, interacted with the ratio of property tax revenues to the total revenue that is not earmarked for specific purposes in the primary and secondary markets. A one-standard deviation increase in the weighted FWI results in an additional 6.6-basis point increase in municipal spreads post-2014 in the primary market for each one-unit increase in property tax reliance. In the secondary market, point estimates similarly suggest that greater reliance on property tax revenues is associated with higher spreads from future wildfire risks, though the effect is not statistically significant.

[Table 4 Here]

We also examine whether 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 use the proportion of the population identifying as non-white to capture the racial minority status of each district. Furthermore, we control for district-level median household income to isolate racial impacts from the confounding effects of socioeconomic status on distributional outcomes. Panel B of Table 4 indicates that wildfire risks are associated with significantly larger credit spreads in districts with higher non-white population shares even after controlling for income levels.

Third, we extend our sample to include transactions in lower wildfire risk areas, specifically the Northeast, Southeast, Midwest, and Northern Great Plains regions.[26] Appendix Table A16 and Table A17 reestimate the main regression with this sample. The results indicate significant capitalization of future wildfire risk changes also on average across the continental United States.[27]

Fourth, we assess the association between municipal credit spreads and projected fire risk changes under the assumption that market participants expected the more ambitious SSP2-4.5 global climate policy scenario. Appendix Table A18 reestimates the main regression with the weighted FWI based on the SSP2-4.5 scenario in both the primary and secondary market. Applying a moderate scenario attenuates the pricing of projected fire risk changes in municipal bond markets. The secondary market continues to exhibit a statistically discernible impact, although the magnitude is roughly half that of the benchmark analysis with the SSP5-8.5 scenario. In the primary market, the association is no longer statistically significant. The difference in results to the benchmark is intuitive: Viewed through a lens of low warming expectations, we see less of a clear risk premium as more of the observed bond

[26]Since some states have more transactions in our data than others (see Table A15), this regression weights by the inverse of the number of bonds in its state and year as in Table 2-Table 3 Columns (4) and (6).

[27]Further analysis suggests that this average effect is largely driven by the benchmark regions, however, whereas heat appears to play a more dominant role in the Eastern United States.

price differences are attributed to noise vs. rising warming risk.

Fifth, we extend our analysis to secondary market county bonds in the Northwest, Southwest, and Southern Great Plains to examine whether similar pricing patterns are observable in a broader set of general obligation municipal bonds. We construct county-level weighted FWI and HI measures following the method delineated in section 2. Our regression model includes state-by-trade-year-month and county-by-maturity-calendar-date-group fixed effects. To account for term structure and economic conditions, we include interactions between the log of years-to-maturity and trade-year indicators, while controlling for bond price volatility, county-level unemployment rates, and income per capita. Appendix Table A19 presents the year-by-year and post-2014 impacts of wildfire risk changes on the credit spreads of county bonds in the secondary market. In column (1), consistent with the patterns observed for school districts in Table 3, we find that credit spreads reflect wildfire risks in the late 2010s.[28] Appendix Figure A4 visualizes the year-by-year estimates in Column (1). Our results for county bonds remain robust to alternative weighting schemes (Column 2) and the inclusion of heat risks (Columns 3–4). In sum, our findings indicate that wildfire risk increases are priced into a wider class of general obligation bonds beyond the education sector confirming that the fiscal costs of climate-driven wildfire risk changes are generalized phenomena in the Western United States.

Finally, in Appendix E, 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.

[28]Due to data limitations, we are unable to control for certain bond-specific covariates, such as insurance, sinking fund provisions, callability, bond age, or turnover. Indeed, our results on county bonds closely mirror the parsimonious specification in Column (2) of Table 3, where we only account for time and unit fixed effects.

4 Conclusion

This paper examines the financial and economic consequences of climate-driven wildfire risk changes in the context of the US municipal bond market, an area of increasing policy concern.[29] 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, 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 sometimes failed to detect economically significant impacts, such as we see in our analysis. Our analysis also offers a new strategy for identifying the impacts of climatic risks that are already changing in the near and medium term by deriving *bond*-level measures of risk changes that vary even within a municipality across bonds and over time, permitting the inclusion of rich fixed effects.

Our results also suggest that future wildfire risk changes have larger effects on districts with higher minority population shares and potentially those with more reliance on local revenue sources. These findings add to the emerging evidence on the disproportionate fiscal costs of climate change facing vulnerable populations (e.g., Jerch et al., 2023; Lopez et al., 2025; 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, 2024). Whether and which risk-sharing innovations could aid US municipalities facing

[29] "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.

growing climate risks is thus an important area for future research.

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Table

Panel A: Steps to cleaning municipal bond data

Primary market	
	# of Issues
Full RDP Sample (Federally tax-exempt school district bonds)	1,016,775
Remove clerical errors	938,179
Drop issues with a time to maturity greater than 30 years	937,348
Drop issues with a time-to-maturity of less than one year	897,707
Drop missing coupon frequencies and select semiannual bonds	870,212
Merge with MMA benchmark yield	724,112
Merge with climate risks and other socioeconomic data	691,990
Drop issues for which the sales method is not available	595,888
Select bonds issued in the NW, SW, and SGP regions	208,212
Select bonds issued in counties with more than one school district	150,002

Secondary market	
	# of Trades
Full MSRB sample	145,451,842
Select federally tax-exempt school district bonds	23,062,421
Drop pre-refunded bonds	13,517,206
Remove clerical errors and select bonds traded at least 10 times	12,249,937
Drop bonds with a time to maturity greater than 30 years	12,188,491
Drop trades during the last year before maturity	11,355,903
Drop trades during the first three months after the issuance	8,161,737
Drop missing coupon frequencies and select semiannual bonds	7,211,834
Construct a monthly panel and merge with MMA benchmark yield	1,269,731
Merge with climate risks and other socioeconomic data	1,141,303
Select bonds issued in the NW, SW, and SGP regions	531,654
Select bonds issued in counties with more than one school district	406,635

Panel B: Summary statistics

Primary market			
	Mean	Std. Dev.	Observations
Fire Risk	4.96	5.79	147,711
Yield-To-Maturity	2.82	1.29	147,711
Spread (basis points)	33.57	43.12	147,711
Time to Maturity (years)	10.29	6.48	147,711
Face Issued Total (Millions USD)	2.03	7.47	147,711
$\mathbb{I}${Insured}	0.31	0.46	147,711
$\mathbb{I}${Callable}	0.51	0.50	147,711
$\mathbb{I}${Sinkable}	0.08	0.27	147,711
$\mathbb{I}${Competitive}	0.40	0.49	147,711

Secondary market			
	Mean	Std. Dev.	Observations
Fire Risk	4.47	5.61	393,573
Yield-To-Maturity	2.38	1.22	393,573
Spread (basis points)	53.56	62.20	393,573
Time to Maturity (years)	7.73	6.22	393,573
Bond Age (years)	3.05	2.73	393,573
Monthly Trading Volume (Thousands USD)	605.45	2,695.54	393,573
Monthly Turnover	0.21	0.44	393,573
Monthly Standard Deviation of Price	0.62	0.66	393,573
$\mathbb{I}${Insured}	0.35	0.48	393,573
$\mathbb{I}${Callable}	0.42	0.49	393,573
$\mathbb{I}${Sinkable}	0.09	0.28	393,573

Table 1: Sample construction

This table summarizes the sample construction for the primary and secondary municipal school district bond market analyses. Panel A outlines the process of cleaning the municipal bond data. Potential clerical errors include trades without prices, those priced above $150 or below $50 per $100 par value, and those with coupon rates exceeding 20%. See section 2 for details on each step. The final sample in the secondary market analysis comprises 393,573 bond-month trades spanning from 2005 to 2020, with 50,457 bonds issued by 1,475 school districts. The primary market sample consists of 147,711 bonds issued by 1,854 school districts, spanning from 2001 to 2021. Panel B reports the summary statistics for the variables used in the final sample. Fire Risk is the maturity-calendar-date-group-matched weighted FWI. 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 and the issue price for the secondary and primary markets, respectively. 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 for the secondary market. Monthly Trading Volume is the sum of the par value traded in the bond-year-month for the secondary market. Face-issued total is the par value for the primary market. Monthly Turnover is the ratio of Monthly Trading Volume to the total face value in the bond-year-month for the secondary market. Monthly Standard Deviation of Price denotes the standard deviation of quoted prices (per $100 par value) within the bond-year-month for the secondary market. $\mathbb{I}${Insured}, $\mathbb{I}${Callable}, and $\mathbb{I}${Sinkable} denote the insurance, callability, and sinkability status, respectively. $\mathbb{I}${Competitive} denotes the sales method by which the bond is traded, either through negotiation or competitive bidding.

	1	2	3	4	5	6
Δ Fire	-0.272					
	(0.806)					
Δ Fire × 𝕀(Year = 2001)	0.030	-2.718	3.752***	1.897	3.086**	1.076
	(1.616)	(1.898)	(1.149)	(3.695)	(1.386)	(3.443)
Δ Fire × 𝕀(Year = 2002)	1.987	-2.602	4.957*	2.937	3.664**	2.795
	(2.387)	(2.696)	(2.833)	(3.001)	(1.696)	(2.838)
Δ Fire × 𝕀(Year = 2003)	-0.392	-9.829***	-1.073	-4.524	-0.854	-0.215
	(2.080)	(2.260)	(1.793)	(3.386)	(2.202)	(4.683)
Δ Fire × 𝕀(Year = 2004)	-1.616	-4.420***	1.222	6.486	0.806	1.692
	(1.293)	(1.536)	(1.105)	(4.029)	(1.197)	(2.609)
Δ Fire × 𝕀(Year = 2006)	0.590	0.859	0.847	-0.379	0.971	-1.533
	(0.663)	(1.492)	(0.847)	(1.370)	(0.800)	(1.656)
Δ Fire × 𝕀(Year = 2007)	0.581	1.765	0.657	1.655	0.307	0.811
	(1.234)	(1.272)	(0.932)	(1.745)	(0.823)	(1.727)
Δ Fire × 𝕀(Year = 2008)	-3.477**	-0.948	0.355	-2.855	-0.719	-7.685***
	(1.699)	(1.476)	(1.391)	(1.747)	(1.063)	(2.375)
Δ Fire × 𝕀(Year = 2009)	-1.432	-3.993*	-8.569***	-10.091***	-8.219***	-11.880***
	(2.118)	(2.313)	(2.550)	(3.496)	(1.621)	(3.075)
Δ Fire × 𝕀(Year = 2010)	4.749***	7.305***	-1.587	-1.886	-1.917**	-3.072
	(1.625)	(1.519)	(1.445)	(2.816)	(0.975)	(2.224)
Δ Fire × 𝕀(Year = 2011)	2.403	4.157**	-2.597	-2.626	-2.950**	-4.566
	(1.933)	(1.955)	(1.701)	(2.327)	(1.362)	(2.932)
Δ Fire × 𝕀(Year = 2012)	9.831***	11.720***	-1.337	-2.871*	-0.677	-3.834*
	(1.695)	(1.515)	(1.033)	(1.469)	(1.107)	(2.043)
Δ Fire × 𝕀(Year = 2013)	9.568***	12.961***	0.627	-1.090	0.292	-3.155
	(1.531)	(2.295)	(0.873)	(1.382)	(0.919)	(2.099)
Δ Fire × 𝕀(Year = 2014)	14.264***	15.903***	1.384*	-0.435	0.860	-2.609
	(1.288)	(1.523)	(0.791)	(1.511)	(0.890)	(1.997)
Δ Fire × 𝕀(Year = 2015)	16.023***	19.506***	4.729***	2.406	5.453***	1.977
	(1.260)	(1.586)	(0.776)	(1.630)	(0.877)	(1.915)
Δ Fire × 𝕀(Year = 2016)	20.720***	25.788***	6.149***	5.252***	6.335***	4.549**
	(1.778)	(1.780)	(0.753)	(1.559)	(0.812)	(2.073)
Δ Fire × 𝕀(Year = 2017)	20.521***	27.404***	6.645***	6.325***	6.805***	5.050**
	(1.453)	(1.653)	(0.926)	(1.694)	(0.910)	(1.979)
Δ Fire × 𝕀(Year = 2018)	19.757***	30.223***	7.380***	6.672***	7.513***	4.509**
	(1.633)	(1.956)	(0.961)	(1.782)	(0.920)	(2.264)
Δ Fire × 𝕀(Year = 2019)	26.401***	37.945***	11.413***	11.010***	12.575***	9.874***
	(2.469)	(1.977)	(1.092)	(2.031)	(0.963)	(2.149)
Δ Fire × 𝕀(Year = 2020)	23.916***	35.835***	11.200***	12.296***	11.507***	11.217***
	(2.099)	(2.292)	(1.229)	(2.408)	(1.100)	(2.427)
Δ Fire × 𝕀(Year = 2021)	20.546***	29.463***	6.988***	8.307***	7.309***	6.195***
	(1.769)	(1.882)	(0.976)	(1.971)	(1.054)	(2.381)
Observation	147,711	147,711	147,711	147,711	206,823	206,823
R^2	0.612	0.800	0.872	0.880	0.873	0.880
Δ Fire	4.410***					
	(0.720)					
Δ Fire × 𝕀(Year >= 2015)	16.261***	19.762***	7.103***	8.053***	7.951***	9.128***
	(1.068)	(1.038)	(0.542)	(1.246)	(0.457)	(0.914)
Observation	147,711	147,711	147,711	147,711	206,823	206,823
R^2	0.608	0.795	0.872	0.879	0.872	0.879
Mean Spread (basis points)	33.57	33.57	33.57	33.57	33.57	33.57
County-by-Issue-Year-Month Fixed Effects	Y	Y	Y	Y	N	N
County/District-by-Issue-Year-Month Fixed Effects	N	N	N	N	Y	Y
District-by-Maturity-Calendar-Date-Group Fixed Effects	N	Y	Y	Y	Y	Y
Controls	N	N	Y	Y	Y	Y
Weights	N	N	N	Y	N	Y
More Than One District Per County	Y	Y	Y	Y	N	N
Cluster for Standard Error	County	County	County	County	District	District
Number of Districts	1,854	1,854	1,854	1,854	2,938	2,938

Table 2: Effect of wildfire risk changes on municipal credit spreads in the primary market

This table reports the year-by-year and post-2014 impact of wildfire risk increases on municipal spreads in the primary market, as described by Equation 5 and Equation 6. 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, calculated from its issue price, and its maturity-matched Municipal Market Analytics (MMA) yield benchmarks in basis points, based on the issue date. Maturity calendar dates are grouped into intervals of 10 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-39), and the weighted FWIs are calculated for each decennial period. We define ΔFire as the difference between the maturity-calendar-date-group-matched future FWI 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 county-by-issue-year-month fixed effects. It also contains the log of the number of years before the maturity date and insurance status interacted with the issue year indicator. In addition, we control for the bond's log of face value, its sales method (negotiated or competitive), its callability and sinkability status, as well as standardized revenues from local sources. Column (1) includes county-by-issue-year-month fixed effects. Column (2) additionally controls for district-by-maturity-calendar-date-group fixed effects. Column (3) presents the benchmark specification including both fixed effects and additional covariates. Column (4) weights each observation by the inverse of the count of distinct bonds within each state for a specific trade year. Column (5) additionally includes bonds issued in counties that contain only one district or span across two counties. Column (6) removes geographic restrictions and applies the weights of Column (4). To account for the non-nested structure between certain districts and counties, we cluster standard errors at the district level. Furthermore, we employ county-year-month fixed effects for districts nested within a single county, while applying district-year-month fixed effects for those spanning multiple counties.

	1	2	3	4	5	6
Δ Fire	1.713					
	(1.467)					
Δ Fire × 𝕀(Year = 2006)	3.025***	2.200	1.071	4.730*	1.050	2.402
	(0.804)	(1.453)	(1.261)	(2.565)	(1.323)	(2.268)
Δ Fire × 𝕀(Year = 2007)	3.958**	1.372	1.656	2.982*	1.811	2.751
	(1.712)	(1.292)	(1.823)	(1.531)	(1.598)	(1.877)
Δ Fire × 𝕀(Year = 2008)	1.257	-2.422	-2.460	0.046	-3.280	-2.938
	(3.600)	(2.253)	(2.712)	(2.259)	(2.400)	(2.797)
Δ Fire × 𝕀(Year = 2009)	3.504	-1.453	-6.658	-7.174	-7.554**	-10.351**
	(8.363)	(5.793)	(5.421)	(4.472)	(3.657)	(4.403)
Δ Fire × 𝕀(Year = 2010)	8.296	1.969	-5.295	-5.245	-5.556*	-7.652**
	(7.223)	(4.577)	(3.694)	(3.327)	(2.899)	(3.423)
Δ Fire × 𝕀(Year = 2011)	8.808	1.481	-5.248	-5.167	-6.200*	-8.242**
	(5.814)	(3.866)	(3.194)	(3.402)	(3.196)	(3.698)
Δ Fire × 𝕀(Year = 2012)	18.938***	10.192***	0.189	0.935	0.135	-0.060
	(4.570)	(3.580)	(2.741)	(2.939)	(2.390)	(2.693)
Δ Fire × 𝕀(Year = 2013)	12.717***	4.725	-1.806	0.788	-1.896	-0.811
	(2.604)	(2.919)	(2.988)	(2.947)	(2.382)	(2.491)
Δ Fire × 𝕀(Year = 2014)	12.005***	4.184	0.074	1.457	0.442	1.236
	(1.890)	(2.629)	(2.648)	(2.505)	(2.281)	(2.326)
Δ Fire × 𝕀(Year = 2015)	12.473***	5.115*	3.827	4.900	4.524*	4.515*
	(1.657)	(2.679)	(2.560)	(3.102)	(2.338)	(2.531)
Δ Fire × 𝕀(Year = 2016)	17.172***	11.549***	5.191*	5.966	6.031**	5.760**
	(1.521)	(2.793)	(2.644)	(3.671)	(2.370)	(2.670)
Δ Fire × 𝕀(Year = 2017)	15.021***	11.638***	5.436*	6.970*	6.483***	6.831**
	(1.450)	(2.816)	(2.801)	(3.716)	(2.457)	(2.698)
Δ Fire × 𝕀(Year = 2018)	13.401***	12.335***	5.687**	6.440*	6.759***	6.439**
	(1.447)	(2.756)	(2.767)	(3.671)	(2.442)	(2.686)
Δ Fire × 𝕀(Year = 2019)	18.022***	19.784***	9.142***	10.741***	10.542***	11.523***
	(1.629)	(2.791)	(2.719)	(3.643)	(2.476)	(2.637)
Δ Fire × 𝕀(Year = 2020)	19.988***	21.527***	9.641***	11.126***	11.143***	11.958***
	(1.652)	(2.912)	(2.965)	(3.889)	(2.488)	(2.605)
Observation	393,573	393,573	393,573	393,573	505,218	505,218
R^2	0.325	0.518	0.684	0.637	0.690	0.650
Δ Fire	11.193***					
	(3.795)					
Δ Fire × 𝕀(Year >= 2015)	7.221**	8.820***	7.961***	6.954***	9.102***	8.142***
	(3.538)	(1.437)	(1.070)	(1.625)	(1.105)	(1.290)
Observation	393,573	393,573	393,573	393,573	505,218	505,218
R^2	0.323	0.515	0.683	0.636	0.689	0.649
Mean Spread (basis points)	53.56	53.56	53.56	53.56	53.56	53.56
County-by-Trade-Year-Month Fixed Effects	Y	Y	Y	Y	N	N
County/District-by-Trade-Year-Month Fixed Effects	N	N	N	N	Y	Y
District-by-Maturity-Calendar-Date-Group Fixed Effects	N	Y	Y	Y	Y	Y
Controls	N	N	Y	Y	Y	Y
Weights	N	N	N	Y	N	Y
More Than One District Per County	Y	Y	Y	Y	N	N
Cluster for Standard Error	County	County	County	County	District	District
Number of Districts	1,475	1,475	1,475	1,475	2,012	2,012

Table 3: Effect of wildfire risk changes on municipal credit spreads in the secondary market

This table reports the year-by-year and post-2014 impact of wildfire risk increases on municipal spreads in the secondary market, as described by Equation 5 and Equation 6. 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, 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 10 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-39), and the weighted FWIs are calculated for each decennial period. We define ΔFire as the difference between the maturity-calendar-date-group-matched future FWI 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 county-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, its callability and sinkability status, as well as standardized revenues from local sources. Column (1) includes county-by-trade-year-month fixed effects. Column (2) additionally controls for district-by-maturity-calendar-date-group fixed effects. Column (3) presents the benchmark specification including both fixed effects and additional covariates. Column (4) weights each observation by the inverse of the count of distinct bonds within each state for a specific trade year. Column (5) additionally includes bonds issued in counties that contain only one district or span across two counties. Column (6) removes geographic restrictions and applies the weights of Column (4). To account for the non-nested structure between certain districts and counties, we cluster standard errors at the district level. Furthermore, we employ county-year-month fixed effects for districts nested within a single county, while applying district-year-month fixed effects for those spanning multiple counties.

Panel A: Local dependence

	Primary	Secondary
Δ Fire $\times$ $\mathbb{I}$(Year >= 2015)	4.578***	6.734***
	(0.768)	(1.752)
Δ Fire $\times$ $\mathbb{I}$(Year >= 2015) $\times$ LocDep	6.585***	3.074
	(1.891)	(3.946)
Observations	147,699	393,445
R^2	0.872	0.683
County-by-Issue/Trade-Year-Month Fixed Effects	Y	Y
District-by-Maturity-Calendar-Date-Group Fixed Effects	Y	Y
Controls	Y	Y

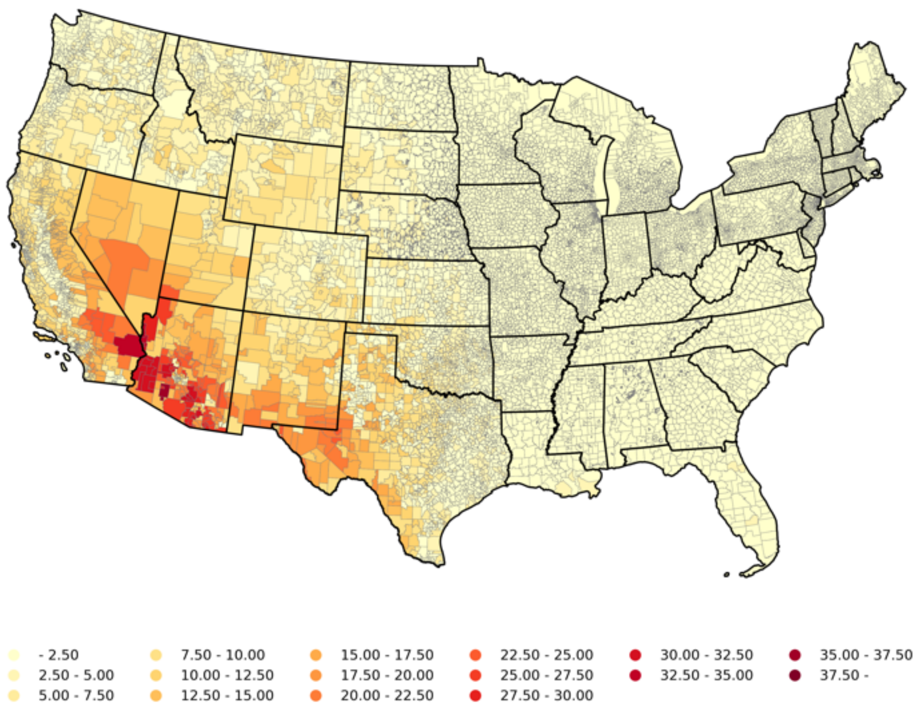
Panel B: Minority

	FWI	
	Primary	Secondary
Δ Fire $\times$ $\mathbb{I}$(Year >= 2015)	3.535	-1.302
	(2.633)	(5.508)
Δ Fire $\times$ $\mathbb{I}$(Year >= 2015) $\times$ Minor	0.063**	0.120*
	(0.030)	(0.070)
Δ Fire $\times$ $\mathbb{I}$(Year >= 2015) $\times$ log(Median Income)	1.141	3.093
	(1.461)	(2.404)
Observations	146,327	392,522
R^2	0.872	0.683
County-by-Issue/Trade-Year-Month Fixed Effects	Y	Y
District-by-Maturity-Calendar-Date-Group Fixed Effects	Y	Y
Controls	Y	Y

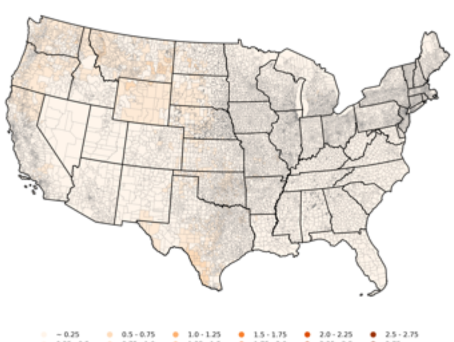
Table 4: Effect of wildfire risk changes on municipal credit spreads - Heterogeneity analyses

This table reports the heterogeneous impacts of wildfire risk increases on municipal spreads in the primary and secondary markets post-2014, as outlined in Equation 6 in which fire risk changes are further interacted with a heterogeneity index. 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. LocDep is the ratio of property tax revenues to total revenue which is not earmarked for specific purposes. Minor is the share of the non-white population. Median Income is the average of median household income (in $10,000s, 2017 USD). 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 10 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-39), and the weighted FWIs are calculated for each decennial period. We define ΔFire as the difference between the maturity-calendar-date-group-matched future FWI 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 county-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 year indicator, its callability and sinkability status, as well as standardized revenues from local sources. For the primary market analysis, we further control for the bond's log face value and its sales method (negotiated or competitive). For the secondary market analysis, we control for the number of years since issuance, the bond's monthly trading volume relative to its face value, and the monthly standard deviation of its prices.

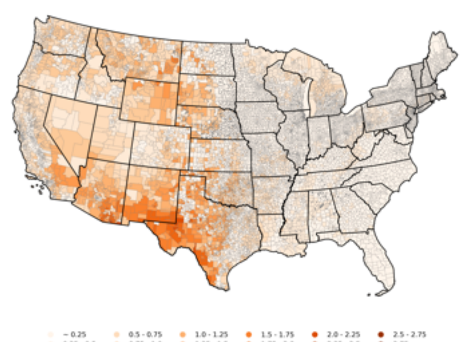
Figure



(a) Weighted FWI (2000-2009)



(b) Difference (2020-2029 minus 2000-2009)



(c) Difference (2040-2049 minus 2000-2009)

Figure 1: Economic wildfire risks by school district under high emissions scenario (SSP5-8.5)

This figure maps school districts' percentage of housing units exposed to fire footprints. We first compute the weighted Canadian Forest Fire Weather Index (FWI), based on Equation 1, along with their changes over time. 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.

Sonoma Valley Unified

Time-to-Maturity (years)

Issue Y-M	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
2005-07	0.00	0.00	0.00	0.00	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10															
2007-05	0.00	0.00	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.19	0.19	0.19	0.19	0.19	0.19											
2015-04	0.10	0.10	0.10	0.10		0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.35	0.35	0.35	0.35											
2015-05	0.10	0.10	0.10	0.10	0.19	0.19	0.19	0.19	0.19	0.19																			
2017-09	0.10	0.19									0.19	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.55		0.55	0.55				0.55
2020-02	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.55		0.55		0.55			0.55		
2020-08			0.19	0.19	0.19	0.19	0.19																						
2021-06		0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.55	0.55									

Santa Rosa Elementary School District

Time-to-Maturity (years)

Issue Y-M	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
2004-05	0.00	0.00	0.00	0.00	0.00	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.06	0.06			0.06				0.06					
2005-08	0.00	0.00	0.00	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06		0.11					
2007-07	0.00	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.06	0.06	0.06	0.06														
2011-07	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.06	0.06			0.06	0.06	0.06														
2013-06	0.03	0.03	0.03	0.03	0.03	0.03	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.11												
2015-02	0.03	0.03	0.03	0.03	0.06	0.06	0.06																						
2016-02	0.03	0.03	0.03	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.11	0.11	0.11	0.11	0.11	0.11										
2016-12	0.03	0.03	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.17	0.17					
2018-06	0.03	0.06	0.06					0.06	0.06	0.06	0.06	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11					0.17				
2021-06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.17	0.17	0.17	0.17							

Figure 2: Within-district variation in economic wildfire risk

This figure visualizes bond issuance and associated economic wildfire risk changes over time for an example of two school districts in Sonoma County, CA. Each row showcases bonds issued by a district at a given issue date ("Issue Y-M") for different maturities (columns). The colors indicate the $\Delta Fire$ over the bond's lifetime. The thick purple outline is an example of a "maturity date group" (bonds maturing in 2030-39).

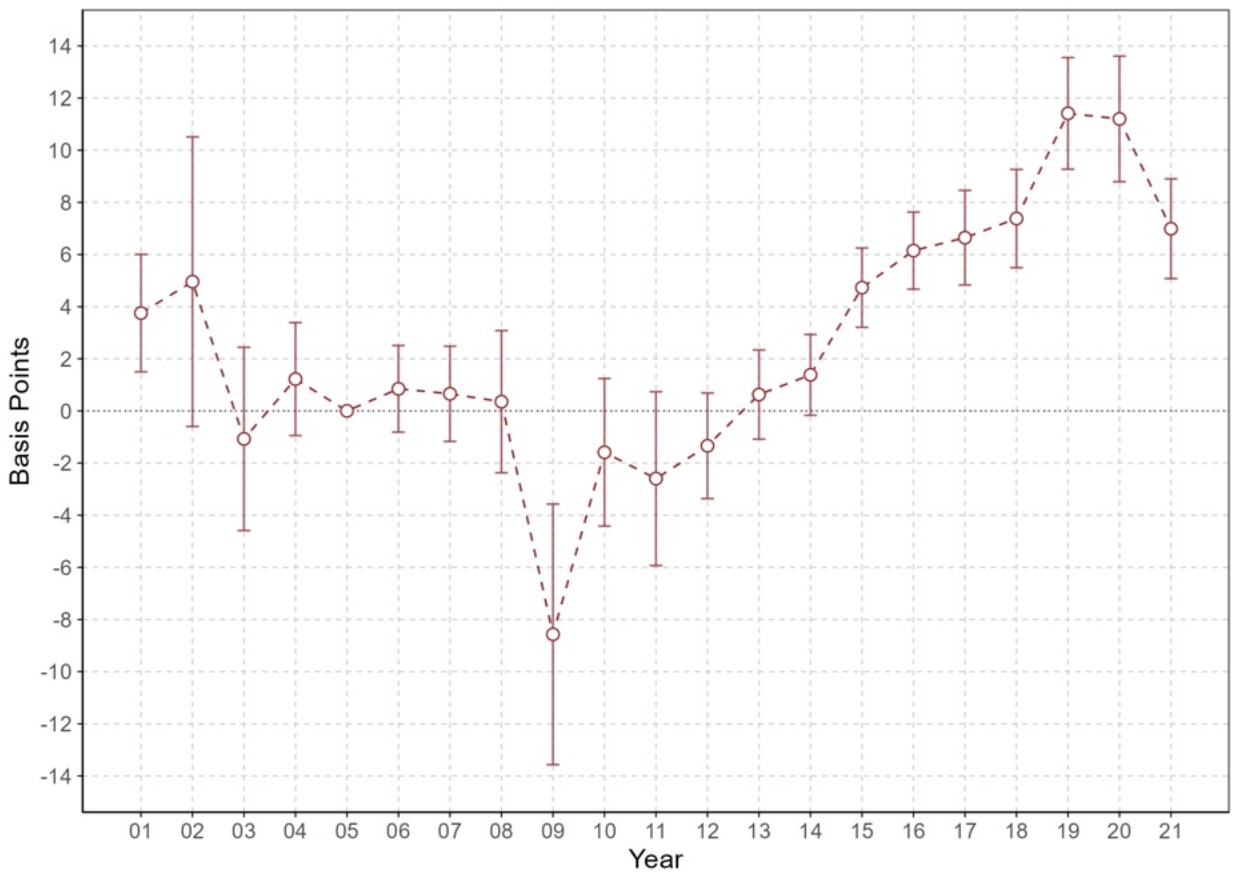


Figure 3: Effect of wildfire risk changes on municipal credit spreads in the primary market

This figure plots the year-by-year impact of wildfire risk increases on the credit spreads of school district bonds in the primary market, as described by Equation 5, with the baseline year set to 2005. 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 its issue price, and its maturity-matched Municipal Market Analytics (MMA) yield benchmarks in basis points, based on the issue date. Maturity calendar dates are grouped into intervals of 10 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-39), and the weighted FWIs are calculated for each decennial period. We define ΔFire as the difference between the maturity-calendar-date-group-matched future FWI 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 county-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 log of face value, its sales method (negotiated or competitive), its callability and sinkability status, as well as standardized revenues from local sources.

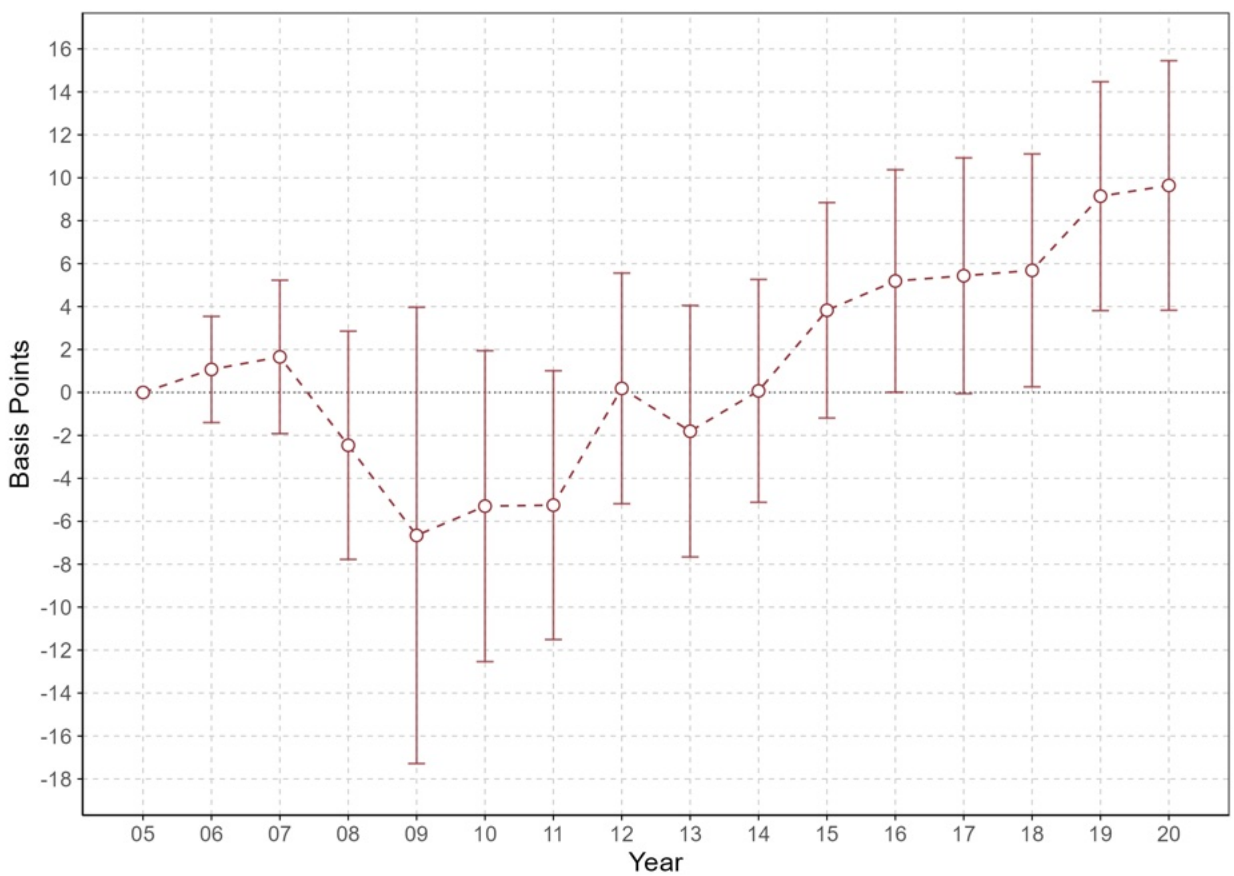


Figure 4: Effect of wildfire risk changes on municipal credit spreads in the secondary market

This figure plots the year-by-year impact of wildfire risk increases on the credit spreads of school district bonds in the secondary market, as described by Equation 5, with the baseline year set to 2005. 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 10 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-39), and the weighted FWIs are calculated for each decennial period. We define ΔFire as the difference between the maturity-calendar-date-group-matched future FWI 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 county-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, its callability and sinkability status, as well as standardized revenues from local sources.

Online Appendix for

Pricing Climate Risks: Evidence from Wildfires and Municipal Bonds

A Name Matching

We compute the weighted FWI 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. 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 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 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 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.[30] 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)

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

(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.

B County Bond Trades in the Secondary Markets

We use the Bloomberg Terminal's Munibond Fixed Income Search (MSRC) to extract the 9-digit CUSIP number for county-issued municipal bonds in the Northwest, the Southwest, and the Southern Great Plains regions from 2005 to 2020. To extend our analysis beyond school districts and examine whether similar pricing patterns are observable in a broader set of municipal issuers, we restrict our sample to county-issued general obligation bonds backed by ad valorem property taxes. We further filter for bonds that are non-federally taxable, non-refunded, and have a semi-annual coupon payment frequency. We then merge with the MSRB Academic Historical Transaction Data to extract secondary market transaction information for county bonds. Following the same data trimming procedure used for school district bonds, we construct a monthly bond-level panel of yield-to-maturity.

We then extract the 6-digit base CUSIP to match each bond issuer with its corresponding 5-digit county FIPS (Federal Information Processing Standards) code, which identifies county governments uniquely. Specifically, within each state, we initially match municipalities using the first one or two words of their names. For any remaining observations, we manually match. Using this match, we merge the county bond transaction data with the economic wildfire and heat risk data. Table A1 summarizes the sample construction and provides summary statistics.

[TABLE A1 HERE]

C Model of Municipal Credit Risks

To interpret the economic magnitude of our spread estimates, we develop a simple discrete-time structural model of municipal credit risk. The exercise is in the spirit of the calibration of Goldsmith-Pinkham et al. (2023), who use a Merton (1974) model to map yield premia from sea level rise into changes in local-government cash flows. Since municipal issuers commonly refinance maturing obligations, we allow the municipality to repay maturing debt using both current fiscal resources and the proceeds from newly issued debt. This rollover feature separates the contractual duration of a bond from the longer horizon over which climate-related fiscal damages may affect repayment.

C.1 Model

A municipality has exogenous tax revenue L_t available for repaying an (exogenously given) initial stock of debt with face value D_1. Below, for simplicity, we will refer to L_t as tax revenue, but one should think of it as pledgeable fiscal capacity. Given initial income L_0, the revenue evolves according to

$$L_{t+1} = e^{g+\epsilon} L_t, \tag{7}$$

where g is the average log growth rate. ϵ, the growth shock, is $\nu_G > 0$ with probability $1 - \pi$ or $\nu_B < 0$ with probability π. We assume $\nu_G = -\nu_B \pi/(1-\pi)$, so that $E[\epsilon] = 0$. Under this restriction, the standard deviation of ϵ is $\sigma = |\nu_B| \sqrt{\pi/(1-\pi)}$. So ν_B governs the volatility of log tax base growth for fixed π. Since we hold the mean fixed at zero, when $\pi < 1/2$ ($\pi > 1/2$), log tax base growth is negatively (positively) skewed. Let G denote $E\left[e^{g+\epsilon}\right]$.

The municipality has a finite horizon of N periods, where each period represents T years. The initial debt D_1 comes due in period $t = 1$, at which point the municipality follows a simple rule-of-thumb: it pays off L_1 of the debt and attempts to roll over the rest into a new one-period (T year) bond with face value D_2. If at market prices the municipality is unable to repay D_1 fully, it simply rolls over the maximal amount and defaults (without recourse) on the rest. This process continues, and in period N the municipality repays $\min(D_N, L_N)$.

In each period the debt is priced by competitive, risk-neutral lenders with the one period discount rate $r_{s_t} \in \{r_L, r_H\}$. $s_t \in \{L, H\}$ follows a Markov process with transition probabilities $p_{ss'}$, where $s, s' \in \{L, H\}$.

Let $MR_t(L_t, r_{s_t})$ denote the maximum possible repayment by the municipality in period t. In the last period, the maximal repayment is simply

$$MR_N(L_N, r_{s_N}) = L_N.$$

In any period $t < N$, the break-even price of debt from the perspective of the lenders is

$$Q_t(D_{t+1}, L_t, r_{s_t}) = \frac{E_t\left[\min\left\{1, \frac{MR_{t+1}(L_{t+1}, r_{s_{t+1}})}{D_{t+1}}\right\}\right]}{1 + r_{s_t}}. \tag{8}$$

And for $t < N$, the maximal repayment is

$$MR_t(L_t, r_{s_t}) = L_t + \max_{D_{t+1}} \left\{D_{t+1} Q_t(D_{t+1}, L_t, r_{s_t})\right\}, \tag{9}$$

which is the available tax revenue plus the maximum amount of debt that can be rolled over at market rates. Plugging Equation 8 into Equation 9, we get

$$MR_t(L_t, r_{s_t}) = L_t + \max_{D_{t+1}} \left\{\frac{E_t\left[\min\left\{D_{t+1}, MR_{t+1}(L_{t+1}, r_{s_{t+1}})\right\}\right]}{1 + r_{s_t}}\right\}.$$

Since D_{t+1} is unbounded, it follows that

$$MR_t(L_t, r_{s_t}) = L_t + \frac{E_t\left[MR_{t+1}(L_{t+1}, r_{s_{t+1}})\right]}{1 + r_{s_t}}, \tag{10}$$

which is current tax revenue plus the expected present value of the maximum repayment in the next period.

Therefore, starting with $MR_N(L_N, r_{s_N}) = L_N$, we can use backwards induction and

Equations 8 and 10 to calculate the functions Q_t and MR_t for all $t = 0, 1, \ldots, N-1$. We can then immediately calculate the actual repayment, the default rate, and the annualized yield:

$$AR_t(D_t, L_t, r_{s_t}) = \min\{D_t, MR_t(L_t, r_{s_t})\} \tag{11}$$

$$Def_t(D_t, L_t, r_{s_t}) = \frac{D_t - AR_t(D_t, L_t, r_{s_t})}{D_t} \tag{12}$$

$$y_t(D_{t+1}, L_t, r_{s_t}) = \left(\frac{1}{Q_t(D_{t+1}, L_t, r_{s_t})}\right)^{\frac{1}{T}} - 1. \tag{13}$$

The evolution of debt solves the equation

$$D_{t+1}(D_t, L_t, r_{s_t})Q_t(D_{t+1}(D_t, L_t, r_{s_t}), L_t, r_{s_t}) = \max\{AR_t(D_t, L_t, r_{s_t}) - L_t, 0\}. \tag{14}$$

So $D_{t+1} = D_{t+2} = \ldots 0$ when $AR_t \leq L_t$, in which case the debt is fully paid with tax revenue. Otherwise, $AR_t > L_t$, which means part of the debt is rolled-over, and we have $D_{t+1} > 0$. The debt level that solves (14) is generally unique because, by Equation 8, the LHS is increasing in D_{t+1}. Suppose, however, that

$$D_{t+1} \geq \bar{D}_t(L_t) \equiv \max_{\epsilon, r_{s_{t+1}}} MR_{t+1}(L_t e^{g+\epsilon}, r_{s_{t+1}}).$$

Any promise level above this threshold will entail some default in all states of the world. Therefore, $D_{t+1}Q_t = \frac{E_t\left[MR_{t+1}(L_{t+1}, r_{s_{t+1}})\right]}{1+r_{s_t}}$ for all $D_{t+1} \geq \bar{D}_t(L_t)$, so if $\bar{D}_t(L_t)$ solves (14), so does any larger promise (without raising more funds today). To deal with this edge case, we assume that the municipality chooses the minimum promise required to raise its required funds. Note that this does not interfere with the existence of a solution because the RHS is at most $\frac{E_t\left[MR_{t+1}(L_{t+1}, r_{s_{t+1}})\right]}{1+r_{s_t}}$.

C.2 Solution

Due to linearity in revenues L_t, we can guess $MR_t(L_t, r_{s_t}) = a_{t,s_t} L_t$. Since $a_{N,s_N} = 1$, we can easily solve via backwards induction.

Plugging the guess into (10), we get

$$a_{t,s_t} = 1 + \frac{E_t\left[a_{t+1,s_{t+1}}\right]}{1 + r_{s_t}} G.$$

Now letting $a_t = (a_{t,L}, a_{t,H})'$, we can write the recusion in matrix form as

$$a_t = \mathbf{1} + M a_{t+1},$$

where

$$M = \begin{pmatrix} p_{LL}/(1 + r_L) & p_{LH}/(1 + r_L) \\ p_{HL}/(1 + r_H) & p_{HH}/(1 + r_H) \end{pmatrix} G.$$

With $a_N = \mathbf{1}$, it follows that

$$\begin{aligned} a_{N-1} &= \mathbf{1} + M\mathbf{1} \\ a_{N-2} &= \mathbf{1} + M\mathbf{1} + M^2\mathbf{1} \\ &\cdots \\ a_0 &= \sum_{n=0}^{N} M^n \mathbf{1}, \end{aligned}$$

or, more generally, $a_t = \sum_{n=0}^{N-t} M^n \mathbf{1}$.

C.3 Calibration and Results

First, we calibrate the model to match the average secondary-market spread of 0.5%. In the data, it is difficult to isolate local revenue earmarked for servicing municipal debt, but we are able to perform a back of the envelope by approximating annual pledged revenues ℓ_τ (where τ denotes a year) using panel data on property taxes from the NCES School District Finance survey. We estimate that $\ln(\ell_\tau/\ell_{\tau-1})$ has mean $\mu^{(1)} = 0.04$, standard deviation $sd^{(1)} = 0.19$, and skewness $\text{skew}^{(1)} = -1.36$. Changing the frequency from 1 year to $T = 7.7$ years (the average time to maturity in our secondary-market sample), we calibrate the parameters of the T-year revenue process $\ln(L_t/L_{t-1})$ as $g = T\mu^{(1)} = 0.31$, $\sigma = \sqrt{T}sd^{(1)} = 0.53$, and $\text{skew}^{(T)} = \text{skew}^{(1)}/\sqrt{T} = -0.49$. From the expression for the skewness of a binary random variable, we then get the T-year downside growth probability $\pi = 0.38$. $\nu_B = -\sigma/\sqrt{\pi/(1-\pi)} = -0.67$ and $\nu_G = -\nu_B\pi/(1-\pi) = 0.41$. [31]

For the risk-free rate, we estimate (via maximum likelihood) a two-state Gaussian hidden Markov model on the daily T-year AAA yield (annualized) over Jan. 2, 2001 through Feb. 2, 2022. With the resulting $\{r_L^A, r_H^A\}$ and transition matrix P^{daily}, we calculate the model values as $r_L = (1 + r_L^A)^T - 1 = 0.15$, $r_H = (1 + r_H^A)^T - 1 = 0.31$, and $P^{(T)} = (P^{daily})^{\mathcal{T}} = \begin{pmatrix} 0.77 & 0.23 \\ 0.70 & 0.30 \end{pmatrix}$, where $\mathcal{T} = 1923$ is approximately the number of observations per year times T. It follows that the unconditional probability of being in the low-rate state is around $p_L = 0.76$.

[31] Our data generating process can be rewritten as

$$\ln\left(\frac{\ell_{i,t+1}}{\ell_{i,t}}\right) = g_i + \varepsilon_{i,t}.$$

Because property tax revenues are the primary source of municipal debt service, we collect panel data on property tax revenues ($\ell_{i,t}$) and long-term and short-term outstanding debt at the end of each fiscal year from the NCES School District Finance survey for the period 2000-2021. We first calculate $\hat{g}_i$ as the average of log differences ($\Delta\ln(\ell_{i,t})$) within each district and then compute the associated residuals: $\hat{\varepsilon}_{i,t} = \Delta\ln(\ell_{i,t}) - \hat{g}_i$. We then calculate the variance and skewness of the pooled residuals and the average cross-district growth rate. We also calculate leverage by dividing the total outstanding debt face value (both long-term and short-term) at the end of the fiscal year by property tax revenues. We find the average leverage for each district and then compute the cross-district average.

Since our β in Equation 6 captures the association between fire risk changes and municipal credit spreads for fire-prone districts, we calculate the above moment only for school districts with fire risks (the weighted FWI for the 2040-2049 period under the SSP5-8.5 scenario) above the median within their respective NCA regions.

Normalizing $L_0 = 1$, for a given N (the total horizon of the municipality), we solve for D_1 such that

$$p_L(y_0(D_1, L_0, r_L) - r_L^A) + (1 - p_L)(y_0(D_1, L_0, r_H) - r_H^A) = .005.$$

That is, we find the initial debt D_1 that matches the average spread of 0.5%. Lastly, we choose the horizon N that generates a D_1 closest to $D_1/L_0 = 2.29$, which is the average value in our sample. The best fit is given by $N = 2$. With this value, $N = 2$, the average spread is matched exactly with $D_1 = 1.77$.

With our simple calibration in hand, we can interpret a spread increase of 8 basis points (0.08%) in three ways: (i) a decline in average growth g, (ii) an increase in the downside probability π, or (iii) an increase in volatility σ.[32] In each case, we vary the particular parameter to exactly match the targeted spread rise. We find that a spread increase of 8 basis points corresponds to a decline in average annual log growth (g/T) of about 14 basis points in both the low and high risk-free rate state. Alternatively, the spread increase can be rationalized as $\Delta\pi = 0.02$, conditional on either risk-free state, that is, an increase of the T-year downside revenue risk probability of around 2 percentage points. Lastly, the spread increase can also be matched with a rise in annualized growth volatility ($\sigma/\sqrt{T}$) of 0.006 (again, regardless of the initial rate state), which is around 3% of the baseline value of 0.19.

We can also put these implied damages in terms of changes in the present value of tax revenues. Let $V_t(L_t, r_{s_t})$ be the present value of tax revenues, the "value" of the municipality. Since $V_N(L_N, r_{s_N}) = L_N$, by backwards induction we have $V_t = MR_t$. When the spread increase is rationalized as a decline in g, present value tax revenues decline by around 1.27% in the low rate state and by 1.20% in the high state. When the spread is rationalized with an increase in the downside probability, net present values fall by 2.17% and 2.02% in the two rate states respectively.

[32] When changing π, we keep ν_B, ν_G, and g fixed, so the mean and volatility of growth also change. When changing σ, we hold constant π and g, so, in this case, the ν payoffs change.

D Economic Heat Risks

The extended Heat Index (HI), developed by Lu and Romps (2022), uses temperature and relative humidity to quantify the physiological heat stress experienced by the human body, based on the thermoregulation model by Steadman (1979). In general, low humidity helps sweat evaporate faster, making high temperatures feel less extreme, while high humidity slows sweat evaporation, making moderate temperatures feel much hotter. A Heat Index greater than 105 indicates that sunstroke, heat cramps, or heat exhaustion are likely, and that heat stroke is possible with prolonged exposure and/or physical activity (NOAA, 2022).

Based on the analytical form by Lu and Romps (2022), we compute the extended Heat Index (HI) using daily maximum air temperature and relative humidity from NASA Earth Exchange Global Daily Downscaled Projections (NASA, 2022). This dataset provides global downscaled climate projections derived from the CMIP6 General Circulation Model (GCM) simulations across the four Tier 1 Shared Socioeconomic Pathways (SSPs). In particular, our analysis uses climate simulations from the Goddard Institute for Space Studies (GISS-E2-1-G) model, assuming a high-emission trajectory represented by SSP5-8.5. Specifically, we construct five different measures of the Heat Index: the seasonal average of daily maximum Heat Index for the summer months (June, July, and August) and the number of summer days with daily maximum Heat Index above 95, 105, 115, and 125 ° F.

Similar to economic wildfire risks, we aggregate Heat Index (HI) data from the census block level to the school district level, using population as weights. For a given school district d, let N_d represent the number of census blocks intersecting with the district. Within each block i, the population is available. We compute the weighted HI for each interval, using the population as weights: for $p \in \{2000-2009, 2010-2019, \cdots, 2040-2049\}$,

$$\text{Weighted HI}_d(p) = \sum_{i=1}^{N_d} \left[\frac{\text{Population}_i}{\sum_{j=1}^{N_d} \text{Population}_j} \times \text{HI}_i(p) \right]. \tag{15}$$

Figure A2 maps the number of summer days with a seasonal average daily maximum HI above 125 for the 2000–2009 period, alongside its projected changes over time across the contiguous United States. In general, the Southern Great Plains, the Southeast, and parts of the Southwest exhibit elevated heat risk levels. Greater increases are expected primarily within the Southeastern regions.

[FIGURE A2 HERE]

E Housing Value Capitalization

The National Center for Education Statistics (NCES) Education Demographic and Geographic Estimates 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 panel by merging this dataset together with our risk map using the Local Education Agency Identification (LEAID). Appendix Table A20 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:

$$Y_{d,c,t} = \lambda_{s,t} + \alpha_d + \sum_{\substack{y=2009 \\ y\neq 2011}}^{2021} \beta_y \Delta \text{FIRE}_d \mathbb{I}(\text{YEAR} = y) + \boldsymbol{\gamma}' \mathbf{X}_{d,t} + \varepsilon_{d,c,t}, \tag{16}$$

for school district d within state s and in year t. Our outcome variable is the median value of owner-occupied housing units.[33] We exclude all observations starting from the year in which they were first impacted by large-scale fires, to isolate the effects of future fire risk changes from the direct impacts of historical fires. 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.

We define ΔFIRE by the difference between mid-century and historic weighted FWI values within a district, standardized to a mean of zero and standard deviation of one. The covariates in $\mathbf{X}$ include the logarithm of 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 state-by-year fixed effects $\lambda_{s,t}$ to control for time-varying economic conditions at the state 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 district level.

Figure A5 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 2016. A one standard-deviation in the weighted FWI 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 2.6% of the average median value of owner-occupied housing units across all school districts.

[33]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).

Appendix Table

Panel A: Steps to Cleaning Municipal Bond Data

	# of Trades
Full MSRB sample	145,451,842
Select federally tax-exempt and non-refunded county bonds backed by ad valorem property taxes in the NW, SW, and SGP regions	472,816
Remove clerical errors and select bonds traded at least 10 times	447,623
Drop bonds with a time to maturity greater than 30 years	447,239
Drop trades during the last year before maturity	413,686
Drop trades during the first three months after the issuance	413,686
Construct a monthly panel and merge with MMA benchmark yield	65,286

Panel B: Summary Statistics

	Mean	Std. Dev.	Observations
Fire Risk	3.60	4.36	65,080
Yield-To-Maturity	2.16	1.16	65,080
Spread (basis points)	44.18	53.00	65,080
Time to Maturity (years)	6.97	5.25	65,080
Monthly Trading Volume (Thousands USD)	994.48	4,275.15	65,080
Monthly Standard Deviation of Price	0.54	0.62	65,080

Table A1: Sample construction

This table summarizes the sample construction for the secondary county bond market analyses. Panel A outlines the process of cleaning the municipal bond data. Potential clerical errors include trades without prices, those priced above $150 or below $50 per $100 par value, and those with coupon rates exceeding 20%. See section 2 for details on each step. The final sample in the secondary market analysis comprises 65,080 bond-month trades spanning from 2005 to 2020, with 7,314 bonds issued by 231 counties. Panel B reports the summary statistics for the variables used in the final sample. Fire Risk is the maturity-calendar-date-group-matched weighted FWI. 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 for the secondary market. 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 for the secondary market. Monthly Trading Volume is the sum of the par value traded in the bond-year-month for the secondary market. Monthly Standard Deviation of Price denotes the standard deviation of quoted prices (per $100 par value) within the bond-year-month for the secondary market.

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 A2: National Climate Assessment (NCA) regions of the contiguous United States

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

	(1)	(2)	(3)	(4)
Δ Fire $\times$ $\mathbb{I}$(Year = 2001)	3.752***	4.066***	7.114***	7.018***
	(1.149)	(1.310)	(1.343)	(1.412)
Δ Fire $\times$ $\mathbb{I}$(Year = 2002)	4.957*	4.276	5.554**	2.835
	(2.833)	(2.689)	(2.316)	(2.264)
Δ Fire $\times$ $\mathbb{I}$(Year = 2003)	-1.073	-2.166	1.137	3.770**
	(1.793)	(1.722)	(1.906)	(1.853)
Δ Fire $\times$ $\mathbb{I}$(Year = 2004)	1.222	2.355*	3.024***	0.658
	(1.105)	(1.349)	(0.871)	(0.942)
Δ Fire $\times$ $\mathbb{I}$(Year = 2006)	0.847	1.026	1.772***	1.539***
	(0.847)	(0.710)	(0.561)	(0.556)
Δ Fire $\times$ $\mathbb{I}$(Year = 2007)	0.657	0.638	0.435	0.469
	(0.932)	(0.877)	(0.905)	(1.094)
Δ Fire $\times$ $\mathbb{I}$(Year = 2008)	0.355	0.397	-1.201	-1.414
	(1.391)	(1.071)	(1.339)	(1.916)
Δ Fire $\times$ $\mathbb{I}$(Year = 2009)	-8.569***	-10.651***	-9.483***	-8.467***
	(2.550)	(2.484)	(2.187)	(2.396)
Δ Fire $\times$ $\mathbb{I}$(Year = 2010)	-1.587	-3.485**	-2.597**	0.329
	(1.445)	(1.426)	(1.107)	(1.557)
Δ Fire $\times$ $\mathbb{I}$(Year = 2011)	-2.597	-2.144	-1.784	-0.155
	(1.701)	(1.814)	(1.596)	(2.005)
Δ Fire $\times$ $\mathbb{I}$(Year = 2012)	-1.337	-1.440	-1.944	0.637
	(1.033)	(1.386)	(1.184)	(1.070)
Δ Fire $\times$ $\mathbb{I}$(Year = 2013)	0.627	0.089	-0.499	3.058***
	(0.873)	(0.813)	(0.851)	(0.875)
Δ Fire $\times$ $\mathbb{I}$(Year = 2014)	1.384*	0.557	-0.266	4.148***
	(0.791)	(0.913)	(0.973)	(0.766)
Δ Fire $\times$ $\mathbb{I}$(Year = 2015)	4.729***	4.703***	4.348***	7.615***
	(0.776)	(0.776)	(0.671)	(0.824)
Δ Fire $\times$ $\mathbb{I}$(Year = 2016)	6.149***	6.828***	5.505***	7.792***
	(0.753)	(0.997)	(0.908)	(0.943)
Δ Fire $\times$ $\mathbb{I}$(Year = 2017)	6.645***	6.249***	5.730***	8.175***
	(0.926)	(1.102)	(0.738)	(0.800)
Δ Fire $\times$ $\mathbb{I}$(Year = 2018)	7.380***	8.340***	5.572***	6.867***
	(0.961)	(1.235)	(0.973)	(0.793)
Δ Fire $\times$ $\mathbb{I}$(Year = 2019)	11.413***	12.679***	10.141***	10.460***
	(1.092)	(1.439)	(1.272)	(1.089)
Δ Fire $\times$ $\mathbb{I}$(Year = 2020)	11.200***	12.496***	9.640***	10.062***
	(1.229)	(1.208)	(1.141)	(1.086)
Δ Fire $\times$ $\mathbb{I}$(Year = 2021)	6.988***	9.475***	7.280***	6.717***
	(0.976)	(1.455)	(1.206)	(0.904)
Observation	147,711	149,108	149,456	148,124
R^2	0.872	0.897	0.882	0.830
Δ Fire $\times$ $\mathbb{I}$(Year >= 2015)	7.103***	7.924***	7.111***	7.242***
	(0.542)	(0.558)	(0.438)	(0.529)
Observation	147,711	149,108	149,456	148,124
R^2	0.872	0.897	0.881	0.829
Mean Spread (basis points)	33.57	33.57	33.57	33.57
Time Fixed Effects	County-by-YM	District-by-YM	District-by-YM	County-by-YM
Unit Fixed Effects	District-by-MG	District-by-MG	County-by-MG	District
Bond-level Controls	Y	Y	Y	Y
District-level Controls	Y	N	N	Y

Table A3: Wildfire risk changes and municipal credit spreads in the primary market - Fixed effect specifications (YM: Year-Month / MG: Maturity-Calendar-Date-Group)

This table reports the year-by-year and post-2014 impact of wildfire risk increases on municipal spreads in the primary market across several fixed effect specifications. 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, calculated from its issue price, and its maturity-matched Municipal Market Analytics (MMA) yield benchmarks in basis points, based on the issue date. Maturity calendar dates are grouped into intervals of 10 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-39), and the weighted FWIs are calculated for each decennial period. We define ΔFire as the difference between the maturity-calendar-date-group-matched future FWI and the historic level, which is standardized to a mean of zero and standard deviation of one. The regression contains the log of the number of years before the maturity date and insurance status interacted with the issue year indicator. In addition, we control for the bond's log of face value, its sales method (negotiated or competitive), its callability and sinkability status. Standardized revenues from local sources are included only when using county-by-year-month fixed effects as district-by-year-month fixed effects absorb the variation in local revenues.

	(1)	(2)	(3)	(4)
Δ Fire $\times$ $\mathbb{I}$(Year = 2006)	1.071	-0.994	-2.457*	0.716
	(1.261)	(1.579)	(1.429)	(0.890)
Δ Fire $\times$ $\mathbb{I}$(Year = 2007)	1.656	2.771	1.415	1.036
	(1.823)	(2.200)	(2.460)	(1.403)
Δ Fire $\times$ $\mathbb{I}$(Year = 2008)	-2.460	-4.102	-5.632*	-3.285
	(2.712)	(3.803)	(3.024)	(2.318)
Δ Fire $\times$ $\mathbb{I}$(Year = 2009)	-6.658	-4.447	-6.363	-6.549
	(5.421)	(7.062)	(5.782)	(5.695)
Δ Fire $\times$ $\mathbb{I}$(Year = 2010)	-5.295	-3.560	-4.114	-5.123
	(3.694)	(5.737)	(3.959)	(3.777)
Δ Fire $\times$ $\mathbb{I}$(Year = 2011)	-5.248	-5.744	-7.615*	-5.069*
	(3.194)	(5.882)	(4.264)	(2.933)
Δ Fire $\times$ $\mathbb{I}$(Year = 2012)	0.189	-2.217	-5.087**	-0.540
	(2.741)	(3.097)	(2.353)	(2.143)
Δ Fire $\times$ $\mathbb{I}$(Year = 2013)	-1.806	-2.037	-6.055***	-4.309**
	(2.988)	(3.059)	(2.316)	(1.755)
Δ Fire $\times$ $\mathbb{I}$(Year = 2014)	0.074	2.443	-1.963	-2.148
	(2.648)	(2.869)	(2.230)	(1.554)
Δ Fire $\times$ $\mathbb{I}$(Year = 2015)	3.827	7.640***	2.223	1.395
	(2.560)	(2.714)	(2.003)	(1.612)
Δ Fire $\times$ $\mathbb{I}$(Year = 2016)	5.191*	9.256***	2.932	2.314
	(2.644)	(2.715)	(2.199)	(1.737)
Δ Fire $\times$ $\mathbb{I}$(Year = 2017)	5.436*	10.274***	3.550	1.763
	(2.801)	(2.940)	(2.470)	(1.803)
Δ Fire $\times$ $\mathbb{I}$(Year = 2018)	5.687**	10.213***	3.460	1.376
	(2.767)	(2.958)	(2.597)	(1.811)
Δ Fire $\times$ $\mathbb{I}$(Year = 2019)	9.142***	16.064***	8.762***	4.349**
	(2.719)	(3.053)	(2.710)	(1.750)
Δ Fire $\times$ $\mathbb{I}$(Year = 2020)	9.641***	17.385***	9.888***	4.869**
	(2.965)	(3.325)	(2.987)	(2.067)
Observation	393,573	361,663	362,028	393,860
R^2	0.684	0.748	0.738	0.657
Δ Fire $\times$ $\mathbb{I}$(Year >= 2015)	7.961***	12.298***	9.770***	5.887***
	(1.070)	(1.804)	(1.555)	(1.564)
Observation	393,573	361,663	362,028	393,860
R^2	0.683	0.747	0.738	0.657
Mean Spread (basis points)	53.56	53.56	53.56	53.56
Time Fixed Effects	County-by-YM	District-by-YM	District-by-YM	County-by-YM
Unit Fixed Effects	District-by-MG	District-by-MG	County-by-MG	District
Bond-level Controls	Y	Y	Y	Y
District-level Controls	Y	N	N	Y

Table A4: Wildfire risk changes and municipal credit spreads in the secondary market - Fixed effect specifications (YM: Year-Month / MG: Maturity-Calendar-Date-Group)

This table reports the year-by-year and post-2014 impact of wildfire risk increases on municipal spreads in the secondary market across several fixed effect specifications. 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, 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 10 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-39), and the weighted FWIs are calculated for each decennial period. We define ΔFire as the difference between the maturity-calendar-date-group-matched future FWI and the historic level, which is standardized to a mean of zero and standard deviation of one. The regression 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, its callability and sinkability status. Standardized revenues from local sources are included only when using county-by-year-month fixed effects as district-by-year-month fixed effects absorb the variation in local revenues.

Panel A: By state

Primary market		
	# of Issues	Percent
AZ	6,995	4.74
CA	63,464	42.96
CO	2,983	2.02
ID	1,029	0.70
KS	3,013	2.04
NM	3,140	2.13
OK	4,814	3.26
OR	2,428	1.64
TX	50,300	34.05
UT	1,801	1.22
WA	7,744	5.24
Total	147,711	100

Secondary market		
	# of Trades	Percent
AZ	29,864	7.59
CA	196,029	49.81
CO	9,817	2.49
ID	1,682	0.43
KS	7,320	1.86
NM	2,923	0.74
OK	2,212	0.56
OR	5,459	1.39
TX	101,657	25.83
UT	6,118	1.55
WA	30,492	7.75
Total	393,573	100

Panel B: By year

Primary market		
	# of Issues	Percent
2001	1,473	1.00
2002	2,718	1.84
2003	1,190	0.81
2004	4,891	3.31
2005	10,101	6.84
2006	9,331	6.32
2007	9,019	6.11
2008	6,903	4.67
2009	5,632	3.81
2010	5,852	3.96
2011	5,518	3.74
2012	7,344	4.97
2013	7,460	5.05
2014	7,845	5.31
2015	11,897	8.05
2016	11,737	7.95
2017	10,126	6.86
2018	7,569	5.12
2019	8,668	5.87
2020	6,630	4.49
2021	5,807	3.93
Total	147,711	100

Secondary market		
	# of Trades	Percent
2005	7,972	2.03
2006	11,623	2.95
2007	12,775	3.25
2008	13,841	3.52
2009	14,894	3.78
2010	15,321	3.89
2011	15,936	4.05
2012	15,134	3.85
2013	20,180	5.13
2014	17,633	4.48
2015	21,654	5.50
2016	28,104	7.14
2017	38,340	9.74
2018	51,492	13.08
2019	52,810	13.42
2020	55,864	14.19
Total	393,573	100

Table A5: Sample composition

Primary Market

	Mean	Std. Dev.	Observations
Fire Risk	4.82	5.47	206,823
Yield-To-Maturity	2.78	1.29	206,823
Spread (basis points)	32.01	41.96	206,823
Time to Maturity (years)	10.11	6.45	206,823
Face Issued Total (Millions USD)	2.01	6.72	206,823
$\mathbb{I}$\{Insured\}	0.28	0.45	206,823
$\mathbb{I}$\{Callable\}	0.49	0.50	206,823
$\mathbb{I}$\{Sinkable\}	0.08	0.26	206,823
$\mathbb{I}$\{Competitive\}	0.44	0.50	206,823

Secondary Market

	Mean	Std. Dev.	Observations
Fire Risk	4.37	5.41	505,218
Yield-To-Maturity	2.35	1.20	505,218
Spread (basis points)	52.10	60.97	505,218
Time to Maturity (years)	7.62	6.14	505,218
Bond Age (years)	2.99	2.68	505,218
Monthly Trading Volume (Thousands USD)	629.32	2,734.27	505,218
Monthly Turnover	0.21	0.44	531,640
Monthly Standard Deviation of Price	0.61	0.65	505,218
$\mathbb{I}$\{Insured\}	0.32	0.47	505,218
$\mathbb{I}$\{Callable\}	0.41	0.49	505,218
$\mathbb{I}$\{Sinkable\}	0.08	0.27	505,218

Table A6: Summary Statistics (No restriction on counties with more than one districts)

This table reports the summary statistics for the variables used in the sample, which includes bonds issued in counties that either contain only one district or span across multiple counties to improve the representativeness of our sample. The final sample in the secondary market analysis comprises 505,218 bond-month trades spanning from 2005 to 2020, with 65,267 bonds issued by 2,012 school districts. The primary market sample consists of 206,823 bonds issued by 2,938 school districts, spanning from 2001 to 2021. Fire Risk is the difference between the maturity-calendar-date-group-matched weighted FWI and the historical level 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 and the issue price for the secondary and primary markets, respectively. 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 for the secondary market. Monthly Trading Volume is the sum of the par value traded in the bond-year-month for the secondary market. Face-issued total is the par value for the primary market. Monthly Turnover is the ratio of Monthly Trading Volume to the total face value in the bond-year-month for the secondary market. Monthly Standard Deviation of Price denotes the standard deviation of quoted prices (per $100 par value) within the bond-year-month for the secondary market. $\mathbb{I}$\{Insured\}, $\mathbb{I}$\{Callable\}, and $\mathbb{I}$\{Sinkable\} denote the insurance, callability, and sinkability status, respectively. $\mathbb{I}$\{Competitive\} denotes the sales method by which the bond is traded, either through negotiation or competitive bidding.

Δ Fire × 𝕀(Year = 2001)	3.934***
	(1.065)
Δ Fire × 𝕀(Year = 2002)	5.119*
	(2.657)
Δ Fire × 𝕀(Year = 2003)	-0.553
	(1.843)
Δ Fire × 𝕀(Year = 2004)	1.917*
	(1.027)
Δ Fire × 𝕀(Year = 2006)	1.545**
	(0.650)
Δ Fire × 𝕀(Year = 2007)	0.648
	(0.961)
Δ Fire × 𝕀(Year = 2008)	1.250
	(1.777)
Δ Fire × 𝕀(Year = 2009)	-7.618***
	(2.434)
Δ Fire × 𝕀(Year = 2010)	-1.172
	(1.311)
Δ Fire × 𝕀(Year = 2011)	-2.607
	(1.922)
Δ Fire × 𝕀(Year = 2012)	-1.061
	(1.284)
Δ Fire × 𝕀(Year = 2013)	1.243
	(0.943)
Δ Fire × 𝕀(Year = 2014)	1.945**
	(0.781)
Δ Fire × 𝕀(Year = 2015)	5.016***
	(0.733)
Δ Fire × 𝕀(Year = 2016)	6.957***
	(0.919)
Δ Fire × 𝕀(Year = 2017)	7.744***
	(1.134)
Δ Fire × 𝕀(Year = 2018)	8.193***
	(0.886)
Δ Fire × 𝕀(Year = 2019)	12.289***
	(1.056)
Δ Fire × 𝕀(Year = 2020)	12.565***
	(1.328)
Δ Fire × 𝕀(Year = 2021)	6.111***
	(0.988)
Observation	124,397
R^2	0.872
Δ Fire × 𝕀(Year >= 2015)	7.061***
	(0.725)
Observation	124,397
R^2	0.871
Mean Spread (basis points)	33.57
County-by-Issue-Year-Month Fixed Effects	Y
District-by-Maturity-Calendar-Date-Group Fixed Effects	Y
Controls	Y

Table A7: Wildfire risk changes and municipal credit spreads in the primary market - Excluding directly-affected school districts

This table reports the year-by-year and post-2014 impact of wildfire risk increases on municipal spreads in the primary market, 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, calculated from its issue price, and its maturity-matched Municipal Market Analytics (MMA) yield benchmarks in basis points, based on the issue date. Maturity calendar dates are grouped into intervals of 10 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-39), and the weighted FWIs are calculated for each decennial period. We define ΔFire as the difference between the maturity-calendar-date-group-matched future FWI 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 county-by-issue-year-month fixed effects. It also contains the log of the number of years before the maturity date and insurance status interacted with the issue year indicator. In addition, we control for the bond's log of face value, its sales method (negotiated or competitive), its callability and sinkability status, as well as standardized revenues from local sources.

Δ Fire $\times$ $\mathbb{I}$(Year = 2006)	1.604
	(1.031)
Δ Fire $\times$ $\mathbb{I}$(Year = 2007)	1.842
	(1.766)
Δ Fire $\times$ $\mathbb{I}$(Year = 2008)	-1.262
	(2.633)
Δ Fire $\times$ $\mathbb{I}$(Year = 2009)	-4.736
	(5.575)
Δ Fire $\times$ $\mathbb{I}$(Year = 2010)	-3.849
	(3.798)
Δ Fire $\times$ $\mathbb{I}$(Year = 2011)	-4.597
	(3.517)
Δ Fire $\times$ $\mathbb{I}$(Year = 2012)	-0.740
	(2.707)
Δ Fire $\times$ $\mathbb{I}$(Year = 2013)	-1.908
	(2.484)
Δ Fire $\times$ $\mathbb{I}$(Year = 2014)	-0.080
	(2.055)
Δ Fire $\times$ $\mathbb{I}$(Year = 2015)	2.853
	(2.327)
Δ Fire $\times$ $\mathbb{I}$(Year = 2016)	3.975
	(2.563)
Δ Fire $\times$ $\mathbb{I}$(Year = 2017)	3.915
	(2.584)
Δ Fire $\times$ $\mathbb{I}$(Year = 2018)	4.272
	(2.591)
Δ Fire $\times$ $\mathbb{I}$(Year = 2019)	7.551***
	(2.720)
Δ Fire $\times$ $\mathbb{I}$(Year = 2020)	8.369***
	(2.837)
Observation	318,184
R^2	0.687
Δ Fire	6.383***
	(1.234)
Observation	318,184
R^2	0.686
Mean Spread (basis points)	53.56
County-by-Trade-Year-Month Fixed Effects	Y
District-by-Maturity-Calendar-Date-Group Fixed Effects	Y
Controls	Y

Table A8: Wildfire risk changes and municipal credit spreads in the secondary market - Excluding directly-affected school districts

This table reports the year-by-year and post-2014 impact of wildfire risk increases on municipal spreads in the secondary market, 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, 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 10 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-39), and the weighted FWIs are calculated for each decennial period. We define ΔFire as the difference between the maturity-calendar-date-group-matched future FWI 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 county-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, its callability and sinkability status, as well as standardized revenues from local sources.

	1	2	3	4	5
Δ HEAT × $\mathbb{I}$(YEAR >= 2015)	6.659***	6.564***	5.079***	0.910	6.320***
	(0.757)	(1.093)	(1.312)	(0.692)	(0.802)
Δ FIRE × $\mathbb{I}$(YEAR >= 2015)	5.525***	5.511***	6.041***	6.894***	4.891***
	(0.743)	(0.780)	(0.627)	(0.574)	(0.740)
Observations	147,711	147,711	147,711	147,711	147,711
R^2	0.873	0.873	0.872	0.872	0.873
Heat Risk	# of summer days with a seasonal average daily maximum heat index above 125	# of summer days with a seasonal average daily maximum heat index above 115	# of summer days with a seasonal average daily maximum heat index above 105	# of summer days with a seasonal average daily maximum heat index above 95	Seasonal average daily maximum heat index
County-by-Issue-Year-Month FE	Y	Y	Y	Y	Y
District-by-Maturity-Calendar-Date-Group FE	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y

Table A9: Wildfire risk changes and municipal credit spreads in the primary market - Heat risks

This table reports the post-2014 impact of wildfire risk increases on municipal spreads in the primary market, including heat risks. 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, calculated from its issue price, and its maturity-matched Municipal Market Analytics (MMA) yield benchmarks in basis points, based on the issue date. Maturity calendar dates are grouped into intervals of 10 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-39), and the weighted FWIs are calculated for each decennial period. We define ΔFIRE as the difference between the maturity-calendar-date-group-matched future FWI and the historic level, which is standardized to a mean of zero and standard deviation of one. Similarly, we define ΔHEAT as the difference between the maturity-calendar-date-group-matched population-weighted Heat Index 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 county-by-issue-year-month fixed effects. It also contains the log of the number of years before the maturity date and insurance status interacted with the issue year indicator. In addition, we control for the bond's log of face value, its sales method (negotiated or competitive), its callability and sinkability status, as well as standardized revenues from local sources.

	1	2	3	4	5
Δ Heat × $\mathbb{I}$(Year >= 2015)	14.592***	12.871***	11.563***	6.811***	18.683***
	(1.659)	(2.179)	(1.908)	(2.602)	(1.542)
Δ Fire × $\mathbb{I}$(Year >= 2015)	6.862***	6.985***	6.585***	5.916***	4.067***
	(1.116)	(1.112)	(1.246)	(1.081)	(0.969)
Observations	393,573	393,573	393,573	393,573	393,573
R^2	0.684	0.684	0.684	0.684	0.685
Heat Risk	# of summer days with a seasonal average daily maximum heat index above 125	# of summer days with a seasonal average daily maximum heat index above 115	# of summer days with a seasonal average daily maximum heat index above 105	# of summer days with a seasonal average daily maximum heat index above 95	Seasonal average daily maximum heat index
County-by-Trade-Year-Month FE	Y	Y	Y	Y	Y
District-by-Maturity-Calendar-Date-Group FE	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y

Table A10: Wildfire risk changes and municipal credit spreads in the secondary market - Heat risks

This table reports the post-2014 impact of wildfire risk increases on municipal spreads in the secondary market, including heat risks. 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, 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 10 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-39), and the weighted FWIs are calculated for each decennial period. We define ΔFire as the difference between the maturity-calendar-date-group-matched future FWI and the historic level, which is standardized to a mean of zero and standard deviation of one. Similarly, we define ΔHeat as the difference between the maturity-calendar-date-group-matched population-weighted Heat Index 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 county-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, its callability and sinkability status, as well as standardized revenues from local sources.

	ΔFire	Population Growth			
		𝕀{Low}	𝕀{Moderate}	𝕀{High}	𝕀{Very High}
Taxbase Risk × 𝕀(Year = 2001)	4.201***		0.176	-	-1.120
	(1.440)		(3.319)	-	(2.697)
Taxbase Risk × 𝕀(Year = 2002)	6.424***	-13.086	1.434	-	-3.756
	(2.408)	(14.721)	(5.197)	-	(4.506)
Taxbase Risk × 𝕀(Year = 2003)	1.392	48.489***	4.678	-	-2.810
	(2.713)	(12.675)	(3.990)	-	(2.591)
Taxbase Risk × 𝕀(Year = 2004)	1.377	-3.702	2.625	-	-2.815
	(1.222)	(15.037)	(3.415)	-	(2.419)
Taxbase Risk × 𝕀(Year = 2006)	0.679	4.685	0.626	-	3.602**
	(0.806)	(11.870)	(2.231)	-	(1.623)
Taxbase Risk × 𝕀(Year = 2007)	0.538	25.304*	-1.342	-	0.833
	(0.931)	(14.119)	(2.013)	-	(1.735)
Taxbase Risk × 𝕀(Year = 2008)	0.542	48.261***	0.482	-	-3.100
	(1.405)	(12.847)	(3.036)	-	(2.774)
Taxbase Risk × 𝕀(Year = 2009)	-7.477***	36.982**	8.048*	-	-1.956
	(2.526)	(16.033)	(4.114)	-	(3.625)
Taxbase Risk × 𝕀(Year = 2010)	-1.255	19.339	1.778	-	-3.239*
	(1.402)	(14.654)	(2.956)	-	(1.941)
Taxbase Risk × 𝕀(Year = 2011)	-3.003*	65.001***	0.548	-	4.811
	(1.667)	(15.039)	(4.322)	-	(3.320)
Taxbase Risk × 𝕀(Year = 2012)	-2.005*	34.490***	0.504	-	9.587***
	(1.152)	(12.730)	(3.306)	-	(2.521)
Taxbase Risk × 𝕀(Year = 2013)	0.451	40.503***	-6.671**	-	1.203
	(0.807)	(14.969)	(3.099)	-	(2.345)
Taxbase Risk × 𝕀(Year = 2014)	1.172	26.518	-1.139	-	6.410***
	(0.776)	(16.211)	(2.674)	-	(2.227)
Taxbase Risk × 𝕀(Year = 2015)	4.704***	44.338***	0.106	-	2.011
	(0.768)	(15.418)	(2.491)	-	(1.914)
Taxbase Risk × 𝕀(Year = 2016)	6.102***	45.337***	2.046	-	-5.971*
	(0.753)	(15.145)	(3.325)	-	(3.413)
Taxbase Risk × 𝕀(Year = 2017)	6.554***	41.240**	2.605	-	1.793
	(0.886)	(17.159)	(3.813)	-	(2.819)
Taxbase Risk × 𝕀(Year = 2018)	7.178***	13.246	-5.617	-	2.649
	(0.977)	(15.086)	(4.384)	-	(4.639)
Taxbase Risk × 𝕀(Year = 2019)	10.670***		-18.385***	-	14.505**
	(1.198)		(5.879)	-	(6.334)
Taxbase Risk × 𝕀(Year = 2020)	10.732***	-33.199***	-15.211**	-	10.194*
	(1.229)	(6.018)	(6.081)	-	(6.016)
Taxbase Risk × 𝕀(Year = 2021)	6.510***		-4.879	-	11.204
	(0.971)		(8.667)	-	(8.151)
Observation			147,711		
R^2			0.873		
Mean Spread (basis points)			33.57		
County-by-Issue-Year-Month Fixed Effects			Y		
District-by-Maturity-Calendar-Date-Group Fixed Effects			Y		
Controls			Y		

Table A11: Wildfire risk changes and municipal credit spreads in the primary market - Population growth rate

This table reports the year-by-year impact of wildfire risk increases and population growth on municipal spreads in the primary market. 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, calculated from its issue price, and its maturity-matched Municipal Market Analytics (MMA) yield benchmarks in basis points, based on the issue date. Maturity calendar dates are grouped into intervals of 10 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-39), and the weighted FWIs are calculated for each decennial period. We define ΔFire as the difference between the maturity-calendar-date-group-matched future FWI and the historic level, which is standardized to a mean of zero and standard deviation of one. The categories 𝕀{Low}, 𝕀{Moderate}, 𝕀{High}, and 𝕀{Very High} correspond to population growth rate in the maturity year within the intervals of $(-\infty, 0.005)$, $[0.005, 0.25)$, $[0.25, 0.4)$, and $[0.4, \infty)$, respectively. The regression includes the bond's district-by-maturity-calendar-date-group fixed effects and county-by-issue-year-month fixed effects. It also contains the log of the number of years before the maturity date and insurance status interacted with the issue year indicator. In addition, we control for the bond's log of face value, its sales method (negotiated or competitive), its callability and sinkability status, as well as standardized revenues from local sources.

		Population Growth			
	ΔFire	𝕀{Low}	𝕀{Moderate}	𝕀{High}	𝕀{Very High}
Taxbase Risk × 𝕀(Year = 2006)	0.867	-146.113***	-2.911	-	3.434
	(1.269)	(25.175)	(2.240)	-	(2.197)
Taxbase Risk × 𝕀(Year = 2007)	1.142	-50.018**	-3.536	-	1.149
	(1.838)	(25.365)	(3.435)	-	(2.843)
Taxbase Risk × 𝕀(Year = 2008)	-2.388		2.227	-	-4.059
	(2.339)		(7.913)	-	(7.443)
Taxbase Risk × 𝕀(Year = 2009)	-4.977		11.058	-	-34.105***
	(3.882)		(10.839)	-	(9.460)
Taxbase Risk × 𝕀(Year = 2010)	-5.017	-25.555	13.062	-	-2.913
	(3.200)	(25.059)	(8.432)	-	(8.087)
Taxbase Risk × 𝕀(Year = 2011)	-4.840*	-79.350***	-2.435	-	-16.390**
	(2.894)	(25.740)	(8.229)	-	(7.785)
Taxbase Risk × 𝕀(Year = 2012)	-2.152	-127.845***	-11.385	-	11.142
	(2.703)	(24.979)	(9.367)	-	(9.153)
Taxbase Risk × 𝕀(Year = 2013)	-4.549	22.544	-11.905	-	15.424**
	(3.001)	(17.460)	(7.568)	-	(7.018)
Taxbase Risk × 𝕀(Year = 2014)	-2.567	88.691***	-15.290**	-	16.319***
	(2.678)	(24.331)	(6.728)	-	(6.152)
Taxbase Risk × 𝕀(Year = 2015)	1.347	23.317	-13.815**	-	14.726**
	(2.662)	(20.133)	(6.115)	-	(5.787)
Taxbase Risk × 𝕀(Year = 2016)	2.742	38.097	-12.123*	-	14.854**
	(2.761)	(28.844)	(6.832)	-	(6.224)
Taxbase Risk × 𝕀(Year = 2017)	2.878	4.740	-16.148**	-	21.823***
	(2.949)	(15.285)	(6.925)	-	(6.232)
Taxbase Risk × 𝕀(Year = 2018)	2.771	35.885***	-14.605**	-	24.672***
	(2.929)	(11.119)	(7.135)	-	(6.329)
Taxbase Risk × 𝕀(Year = 2019)	5.782*	12.768	-22.804***	-	32.727***
	(2.945)	(8.730)	(7.123)	-	(6.531)
Taxbase Risk × 𝕀(Year = 2020)	6.337**		-26.669***	-	30.101***
	(3.042)		(7.529)	-	(7.267)
Observation			393,573		
R^2			0.686		
Mean Spread (basis points)			53.56		
County-by-Trade-Year-Month Fixed Effects			Y		
District-by-Maturity-Calendar-Date-Group Fixed Effects			Y		
Controls			Y		

Table A12: Wildfire risk changes and municipal credit spreads in the secondary market - Population growth rate

This table reports the year-by-year impact of wildfire risk increases and population growth on municipal spreads in the secondary market. 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, 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 10 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-39), and the weighted FWIs are calculated for each decennial period. We define ΔFire as the difference between the maturity-calendar-date-group-matched future FWI and the historic level, which is standardized to a mean of zero and standard deviation of one. The categories 𝕀{Low}, 𝕀{Moderate}, 𝕀{High}, and 𝕀{Very High} correspond to population growth rate in the maturity year within the intervals of $(-\infty, 0.005), [0.005, 0.25), [0.25, 0.4)$, and $[0.4, \infty)$, respectively. The regression includes the bond's district-by-maturity-calendar-date-group fixed effects and county-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, its callability and sinkability status, as well as standardized revenues from local sources.

	(1)	(2)	(3)
Δ Fire × 𝕀(Year = 2001)	3.752***	5.754***	4.771***
	(1.149)	(1.587)	(1.116)
Δ Fire × 𝕀(Year = 2002)	4.957*	9.747**	7.382**
	(2.833)	(4.330)	(3.401)
Δ Fire × 𝕀(Year = 2003)	-1.073	1.028	-0.185
	(1.793)	(2.676)	(1.982)
Δ Fire × 𝕀(Year = 2004)	1.222	2.584	1.865
	(1.105)	(1.996)	(1.165)
Δ Fire × 𝕀(Year = 2006)	0.847	1.125	0.858
	(0.847)	(0.955)	(1.006)
Δ Fire × 𝕀(Year = 2007)	0.657	1.492	2.698***
	(0.932)	(1.195)	(0.835)
Δ Fire × 𝕀(Year = 2008)	0.355	3.619	1.001
	(1.391)	(2.283)	(2.354)
Δ Fire × 𝕀(Year = 2009)	-8.569***	-0.252	-5.334***
	(2.550)	(2.052)	(1.969)
Δ Fire × 𝕀(Year = 2010)	-1.587	2.844	1.012
	(1.445)	(2.759)	(2.897)
Δ Fire × 𝕀(Year = 2011)	-2.597	4.113	2.212
	(1.701)	(2.509)	(2.674)
Δ Fire × 𝕀(Year = 2012)	-1.337	1.643	-0.840
	(1.033)	(2.055)	(2.075)
Δ Fire × 𝕀(Year = 2013)	0.627	0.955	-3.804***
	(0.873)	(1.402)	(1.383)
Δ Fire × 𝕀(Year = 2014)	1.384*	1.853	1.270
	(0.791)	(1.585)	(1.584)
Δ Fire × 𝕀(Year = 2015)	4.729***	7.816***	2.531**
	(0.776)	(0.961)	(1.261)
Δ Fire × 𝕀(Year = 2016)	6.149***	12.145***	8.061***
	(0.753)	(1.213)	(1.605)
Δ Fire × 𝕀(Year = 2017)	6.645***	9.132***	5.429***
	(0.926)	(1.008)	(1.378)
Δ Fire × 𝕀(Year = 2018)	7.380***	12.787***	11.071***
	(0.961)	(1.481)	(2.269)
Δ Fire × 𝕀(Year = 2019)	11.413***	16.719***	15.722***
	(1.092)	(1.698)	(2.448)
Δ Fire × 𝕀(Year = 2020)	11.200***	13.315***	10.449***
	(1.229)	(1.405)	(2.032)
Δ Fire × 𝕀(Year = 2021)	6.988***	9.284***	11.223***
	(0.976)	(1.867)	(2.343)
Δ Forward Fire × 𝕀(Year = 2001)		-4.112	-4.569
		(2.965)	(3.902)
Δ Forward Fire × 𝕀(Year = 2002)		-10.541**	-12.358*
		(5.024)	(6.586)
Δ Forward Fire × 𝕀(Year = 2003)		-4.332	-6.692**
		(3.194)	(2.688)
Δ Forward Fire × 𝕀(Year = 2004)		-2.623	-1.964
		(3.228)	(3.329)
Δ Forward Fire × 𝕀(Year = 2006)		-0.546	-0.379
		(1.449)	(1.935)
Δ Forward Fire × 𝕀(Year = 2007)		-1.942	-5.314**
		(1.728)	(2.240)
Δ Forward Fire × 𝕀(Year = 2008)		-5.204**	-1.810
		(2.228)	(3.988)
Δ Forward Fire × 𝕀(Year = 2009)		-11.492***	-9.662***
		(1.950)	(2.544)
Δ Forward Fire × 𝕀(Year = 2010)		-6.932**	-5.998
		(3.203)	(5.278)
Δ Forward Fire × 𝕀(Year = 2011)		-10.112***	-11.029***
		(3.220)	(3.811)
Δ Forward Fire × 𝕀(Year = 2012)		-4.876*	-3.677
		(2.930)	(3.543)
Δ Forward Fire × 𝕀(Year = 2013)		-0.555	7.551***
		(2.058)	(2.728)
Δ Forward Fire × 𝕀(Year = 2014)		-0.796	-0.674
		(2.260)	(2.997)
Δ Forward Fire × 𝕀(Year = 2015)		-4.963***	2.486
		(1.601)	(2.584)
Δ Forward Fire × 𝕀(Year = 2016)		-10.282***	-4.255
		(2.159)	(3.334)
Δ Forward Fire × 𝕀(Year = 2017)		-3.661***	0.623
		(1.348)	(2.367)
Δ Forward Fire × 𝕀(Year = 2018)		-9.278***	-7.010
		(3.381)	(4.684)
Δ Forward Fire × 𝕀(Year = 2019)		-9.265***	-7.784*
		(2.996)	(4.023)
Δ Forward Fire × 𝕀(Year = 2020)		-2.786	0.982
		(3.715)	(4.438)
Δ Forward Fire × 𝕀(Year = 2021)		-3.472	-10.922**
		(3.771)	(4.457)
Observation	147,711	147,711	143,017
R^2	0.872	0.873	0.870
Mean Spread (basis points)	33.57	33.57	33.57
County-by-Issue-Year-Month Fixed Effects	Y	Y	Y
District-by-Maturity-Calendar-Date-Group Fixed Effects	Y	Y	Y
Controls	Y	Y	Y

Table A13: Wildfire risk changes and municipal credit spreads in the primary market - Wildfire risks beyond maturity dates

This table reports the year-by-year impact of wildfire risk increases on municipal spreads controlling for 10-years-post-maturity risk (column 2) and 20-years-post-maturity risk (column 3) in addition to maturity-year risk. 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.

	(1)	(2)	(3)
Δ Fire × 𝕀(Year = 2006)	1.071	0.976	1.272
	(1.261)	(1.147)	(1.643)
Δ Fire × 𝕀(Year = 2007)	1.656	1.555	1.374
	(1.823)	(1.824)	(1.786)
Δ Fire × 𝕀(Year = 2008)	-2.460	-3.548	-1.672
	(2.712)	(2.915)	(2.730)
Δ Fire × 𝕀(Year = 2009)	-6.658	-6.928	-5.575
	(5.421)	(6.238)	(5.237)
Δ Fire × 𝕀(Year = 2010)	-5.295	-6.561	-4.414
	(3.694)	(4.362)	(3.686)
Δ Fire × 𝕀(Year = 2011)	-5.248	-5.082	-4.612
	(3.194)	(3.990)	(3.199)
Δ Fire × 𝕀(Year = 2012)	0.189	-0.776	1.636
	(2.741)	(3.962)	(2.510)
Δ Fire × 𝕀(Year = 2013)	-1.806	-5.506	-1.621
	(2.988)	(3.991)	(3.033)
Δ Fire × 𝕀(Year = 2014)	0.074	-4.073	0.576
	(2.648)	(3.648)	(2.471)
Δ Fire × 𝕀(Year = 2015)	3.827	1.027	4.399*
	(2.560)	(3.612)	(2.318)
Δ Fire × 𝕀(Year = 2016)	5.191*	1.891	4.911*
	(2.644)	(3.784)	(2.649)
Δ Fire × 𝕀(Year = 2017)	5.436*	2.216	5.909**
	(2.801)	(3.992)	(2.838)
Δ Fire × 𝕀(Year = 2018)	5.687**	2.192	5.625*
	(2.767)	(4.069)	(2.859)
Δ Fire × 𝕀(Year = 2019)	9.142***	7.131*	10.507***
	(2.719)	(4.312)	(3.060)
Δ Fire × 𝕀(Year = 2020)	9.641***	7.342	10.753***
	(2.965)	(4.544)	(3.316)
Δ Forward Fire × 𝕀(Year = 2006)		1.344	0.285
		(2.058)	(1.228)
Δ Forward Fire × 𝕀(Year = 2007)		1.574	-1.077
		(3.000)	(1.223)
Δ Forward Fire × 𝕀(Year = 2008)		4.341	1.774
		(3.564)	(2.288)
Δ Forward Fire × 𝕀(Year = 2009)		2.120	4.360
		(5.142)	(3.760)
Δ Forward Fire × 𝕀(Year = 2010)		4.274	3.499
		(4.835)	(2.736)
Δ Forward Fire × 𝕀(Year = 2011)		1.555	1.009
		(4.289)	(2.564)
Δ Forward Fire × 𝕀(Year = 2012)		4.043	0.761
		(4.839)	(2.935)
Δ Forward Fire × 𝕀(Year = 2013)		8.295**	3.811
		(3.983)	(2.441)
Δ Forward Fire × 𝕀(Year = 2014)		8.879**	3.183
		(4.216)	(2.530)
Δ Forward Fire × 𝕀(Year = 2015)		6.949	2.773
		(4.400)	(2.728)
Δ Forward Fire × 𝕀(Year = 2016)		7.630*	4.020
		(4.362)	(2.809)
Δ Forward Fire × 𝕀(Year = 2017)		7.507	2.702
		(4.661)	(3.073)
Δ Forward Fire × 𝕀(Year = 2018)		7.814	2.897
		(4.770)	(3.196)
Δ Forward Fire × 𝕀(Year = 2019)		5.830	1.745
		(5.342)	(3.687)
Δ Forward Fire × 𝕀(Year = 2020)		6.243	1.774
		(5.238)	(3.500)
Observation	393,573	393,573	373,837
R^2	0.684	0.684	0.673
Mean Spread (basis points)	53.56	53.56	53.56
County-by-Trade-Year-Month Fixed Effects	Y	Y	Y
District-by-Maturity-Calendar-Date-Group Fixed Effects	Y	Y	Y
Controls	Y	Y	Y

Table A14: Wildfire risk changes and municipal credit spreads in the secondary market - Wildfire risks beyond maturity dates

This table reports the year-by-year impact of wildfire risk increases on municipal spreads controlling for 10-years-post-maturity risk (column 2) and 20-years-post-maturity risk (column 3), in addition to maturity-year risk. 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.

Panel A: By state

Primary market		
	# of Issues	Percent
AL	3,296	1.43
AR	12,572	5.47
CT	2,494	1.08
GA	682	0.30
IA	3,370	1.47
IL	15,539	6.76
IN	20,770	9.03
KY	10,658	4.63
LA	742	0.32
MA	4,410	1.92
ME	662	0.29
MI	14,087	6.12
MN	6,747	2.93
MO	9,389	4.08
MS	2,164	0.94
MT	2,122	0.92
NC	444	0.19
ND	1,504	0.65
NE	1,866	0.81
NH	563	0.24
NJ	17,110	7.44
NY	28,503	12.39
OH	12,574	5.47
OK	11	0.00
PA	43,623	18.96
RI	227	0.10
SC	2,930	1.27
SD	544	0.24
TN	2,500	1.09
VA	40	0.02
WI	7,764	3.38
WY	120	0.05
Total	230,027	100

Secondary market		
	# of Trades	Percent
AL	5,855	1.67
AR	1,936	0.55
CT	2,243	0.64
DE	16	0.00
GA	2,802	0.80
IA	1,814	0.52
IL	19,941	5.70
IN	26,750	7.64
KY	12,564	3.59
LA	980	0.28
MA	8,183	2.34
ME	1,028	0.29
MI	36,889	10.54
MN	16,256	4.65
MO	11,655	3.33
MS	1,708	0.49
MT	1,171	0.33
NC	1,002	0.29
ND	1,196	0.34
NE	754	0.22
NH	1,827	0.52
NJ	41,916	11.98
NY	55,518	15.86
OH	19,269	5.51
OK	25	0.01
PA	55,505	15.86
RI	463	0.13
SC	11,177	3.19
SD	56	0.02
TN	2,716	0.78
VA	51	0.01
WI	6,660	1.90
WY	37	0.01
Total	349,963	100

Panel B: By year

Primary market		
	# of Issues	Percent
2001	1,889	0.82
2002	4,211	1.83
2003	1,745	0.76
2004	5,806	2.52
2005	17,993	7.82
2006	14,164	6.16
2007	12,396	5.39
2008	10,212	4.44
2009	11,960	5.20
2010	12,313	5.35
2011	10,500	4.56
2012	14,293	6.21
2013	11,134	4.84
2014	12,593	5.47
2015	15,489	6.73
2016	15,238	6.62
2017	11,929	5.19
2018	9,105	3.96
2019	12,508	5.44
2020	13,360	5.81
2021	11,189	4.86
Total	230,027	100

Secondary market		
	# of Trades	Percent
2005	8,934	2.55
2006	14,018	4.01
2007	14,028	4.01
2008	13,884	3.97
2009	13,988	4.00
2010	14,902	4.26
2011	15,880	4.54
2012	14,171	4.05
2013	17,904	5.12
2014	15,351	4.39
2015	20,015	5.72
2016	25,675	7.34
2017	32,020	9.15
2018	43,894	12.54
2019	41,446	11.84
2020	43,853	12.53
Total	349,963	100

Table A15: Sample composition in NCA regions with low wildfire risks

Δ Fire $\times$ $\mathbb{I}$(Year = 2001)	-0.493
	(3.000)
Δ Fire $\times$ $\mathbb{I}$(Year = 2002)	1.369
	(2.244)
Δ Fire $\times$ $\mathbb{I}$(Year = 2003)	-6.414**
	(2.878)
Δ Fire $\times$ $\mathbb{I}$(Year = 2004)	2.902
	(2.844)
Δ Fire $\times$ $\mathbb{I}$(Year = 2006)	-1.705
	(1.040)
Δ Fire $\times$ $\mathbb{I}$(Year = 2007)	-1.441
	(1.355)
Δ Fire $\times$ $\mathbb{I}$(Year = 2008)	-6.495***
	(2.114)
Δ Fire $\times$ $\mathbb{I}$(Year = 2009)	-13.479***
	(3.320)
Δ Fire $\times$ $\mathbb{I}$(Year = 2010)	-6.663**
	(2.712)
Δ Fire $\times$ $\mathbb{I}$(Year = 2011)	-4.803**
	(1.912)
Δ Fire $\times$ $\mathbb{I}$(Year = 2012)	-4.211***
	(1.609)
Δ Fire $\times$ $\mathbb{I}$(Year = 2013)	-2.214*
	(1.233)
Δ Fire $\times$ $\mathbb{I}$(Year = 2014)	-3.083**
	(1.536)
Δ Fire $\times$ $\mathbb{I}$(Year = 2015)	-0.346
	(1.482)
Δ Fire $\times$ $\mathbb{I}$(Year = 2016)	1.056
	(1.490)
Δ Fire $\times$ $\mathbb{I}$(Year = 2017)	2.722*
	(1.543)
Δ Fire $\times$ $\mathbb{I}$(Year = 2018)	1.914
	(1.525)
Δ Fire $\times$ $\mathbb{I}$(Year = 2019)	5.974***
	(1.659)
Δ Fire $\times$ $\mathbb{I}$(Year = 2020)	6.615***
	(1.814)
Δ Fire $\times$ $\mathbb{I}$(Year = 2021)	4.249***
	(1.514)
Observation	377,738
R^2	0.879
Mean Spread (basis points)	33.57
County-by-Issue-Year-Month Fixed Effects	Y
District-by-Maturity-Calendar-Date-Group Fixed Effects	Y
Controls	Y

Table A16: Wildfire risk changes and municipal credit spreads in the primary market - Contiguous US (CONUS)

This table reports the year-by-year impact of wildfire and heat risk increases on municipal spreads in the primary market, weighting each observation by the inverse of the count of distinct bonds within each state for a specific issue year. 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, calculated from its issue price, and its maturity-matched Municipal Market Analytics (MMA) yield benchmarks in basis points, based on the issue date. Maturity calendar dates are grouped into intervals of 10 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-39), and the weighted FWIs are calculated for each decennial period. We define ΔFire as the difference between the maturity-calendar-date-group-matched future FWI 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 county-by-issue-year-month fixed effects. It also contains the log of the number of years before the maturity date and insurance status interacted with the issue year indicator. In addition, we control for the bond's log of face value, its sales method (negotiated or competitive), its callability and sinkability status, as well as standardized revenues from local sources.

Δ Fire $\times$ $\mathbb{I}$(Year = 2006)	5.094*
	(2.794)
Δ Fire $\times$ $\mathbb{I}$(Year = 2007)	4.790**
	(2.287)
Δ Fire $\times$ $\mathbb{I}$(Year = 2008)	2.099
	(2.427)
Δ Fire $\times$ $\mathbb{I}$(Year = 2009)	-5.852
	(4.009)
Δ Fire $\times$ $\mathbb{I}$(Year = 2010)	-4.309
	(3.252)
Δ Fire $\times$ $\mathbb{I}$(Year = 2011)	-3.516
	(3.248)
Δ Fire $\times$ $\mathbb{I}$(Year = 2012)	1.855
	(2.943)
Δ Fire $\times$ $\mathbb{I}$(Year = 2013)	2.755
	(3.080)
Δ Fire $\times$ $\mathbb{I}$(Year = 2014)	4.658
	(2.990)
Δ Fire $\times$ $\mathbb{I}$(Year = 2015)	6.736**
	(3.293)
Δ Fire $\times$ $\mathbb{I}$(Year = 2016)	7.086**
	(3.561)
Δ Fire $\times$ $\mathbb{I}$(Year = 2017)	8.173**
	(3.601)
Δ Fire $\times$ $\mathbb{I}$(Year = 2018)	7.837**
	(3.609)
Δ Fire $\times$ $\mathbb{I}$(Year = 2019)	11.052***
	(3.572)
Δ Fire $\times$ $\mathbb{I}$(Year = 2020)	12.026***
	(3.887)
Observation	743,536
R^2	0.744
Mean Spread (basis points)	53.56
County-by-Trade-Year-Month Fixed Effects	Y
District-by-Maturity-Calendar-Date-Group Fixed Effects	Y
Controls	Y

Table A17: Wildfire risk changes and municipal credit spreads in the secondary market - Contiguous US (CONUS)

This table reports the year-by-year impact of wildfire and heat risk increases on municipal spreads in the secondary market, weighting each observation by the inverse of the count of distinct bonds within each state for a specific trade year. 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, 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 10 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-39), and the weighted FWIs are calculated for each decennial period. We define ΔFire as the difference between the maturity-calendar-date-group-matched future FWI 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 county-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, its callability and sinkability status, as well as standardized revenues from local sources.

Panel A: Primary market

Δ Fire $\times$ $\mathbb{I}$(Year = 2001)	2.502
	(1.838)
Δ Fire $\times$ $\mathbb{I}$(Year = 2002)	0.134
	(2.135)
Δ Fire $\times$ $\mathbb{I}$(Year = 2003)	-3.937
	(2.420)
Δ Fire $\times$ $\mathbb{I}$(Year = 2004)	0.354
	(1.741)
Δ Fire $\times$ $\mathbb{I}$(Year = 2006)	2.871***
	(0.864)
Δ Fire $\times$ $\mathbb{I}$(Year = 2007)	1.659*
	(0.968)
Δ Fire $\times$ $\mathbb{I}$(Year = 2008)	-1.985*
	(1.092)
Δ Fire $\times$ $\mathbb{I}$(Year = 2009)	-8.309***
	(1.764)
Δ Fire $\times$ $\mathbb{I}$(Year = 2010)	-2.708*
	(1.611)
Δ Fire $\times$ $\mathbb{I}$(Year = 2011)	-3.394**
	(1.627)
Δ Fire $\times$ $\mathbb{I}$(Year = 2012)	-3.270**
	(1.645)
Δ Fire $\times$ $\mathbb{I}$(Year = 2013)	-0.029
	(1.191)
Δ Fire $\times$ $\mathbb{I}$(Year = 2014)	2.056
	(1.284)
Δ Fire $\times$ $\mathbb{I}$(Year = 2015)	-1.853
	(1.254)
Δ Fire $\times$ $\mathbb{I}$(Year = 2016)	-4.572***
	(1.091)
Δ Fire $\times$ $\mathbb{I}$(Year = 2017)	0.839
	(1.443)
Δ Fire $\times$ $\mathbb{I}$(Year = 2018)	-2.850
	(2.096)
Δ Fire $\times$ $\mathbb{I}$(Year = 2019)	-0.933
	(1.266)
Δ Fire $\times$ $\mathbb{I}$(Year = 2020)	0.915
	(2.669)
Δ Fire $\times$ $\mathbb{I}$(Year = 2021)	-1.482
	(2.704)
Observation	147,711
R^2	0.871
Δ Fire $\times$ $\mathbb{I}$(Year >= 2015)	-1.345
	(0.841)
Observation	147,711
R^2	0.871
Mean Spread (basis points)	33.57
County-by-Issue-Year-Month FE	Y
District-by-Maturity-Calendar-Date-Group FE	Y
Controls	Y

Panel B: Secondary market

Δ Fire $\times$ $\mathbb{I}$(Year = 2006)	1.664
	(1.591)
Δ Fire $\times$ $\mathbb{I}$(Year = 2007)	1.842
	(2.214)
Δ Fire $\times$ $\mathbb{I}$(Year = 2008)	-2.171
	(2.984)
Δ Fire $\times$ $\mathbb{I}$(Year = 2009)	-7.573
	(4.765)
Δ Fire $\times$ $\mathbb{I}$(Year = 2010)	-4.794
	(3.951)
Δ Fire $\times$ $\mathbb{I}$(Year = 2011)	-4.251
	(2.737)
Δ Fire $\times$ $\mathbb{I}$(Year = 2012)	2.349
	(2.775)
Δ Fire $\times$ $\mathbb{I}$(Year = 2013)	4.526*
	(2.440)
Δ Fire $\times$ $\mathbb{I}$(Year = 2014)	5.753**
	(2.503)
Δ Fire $\times$ $\mathbb{I}$(Year = 2015)	5.682**
	(2.490)
Δ Fire $\times$ $\mathbb{I}$(Year = 2016)	6.298***
	(2.330)
Δ Fire $\times$ $\mathbb{I}$(Year = 2017)	6.396***
	(2.418)
Δ Fire $\times$ $\mathbb{I}$(Year = 2018)	6.368***
	(2.371)
Δ Fire $\times$ $\mathbb{I}$(Year = 2019)	6.650***
	(2.484)
Δ Fire $\times$ $\mathbb{I}$(Year = 2020)	6.906***
	(2.609)
Observation	393,573
R^2	0.683
Δ Fire $\times$ $\mathbb{I}$(Year >= 2015)	3.830***
	(0.885)
Observation	393,573
R^2	0.683
Mean Spread (basis points)	53.56
County-by-Trade-Year-Month FE	Y
District-by-Maturity-Calendar-Date-Group FE	Y
Controls	Y

Table A18: Wildfire risk changes and municipal credit spreads - Moderate Emissions Scenario (SSP2-4.5)

This table reports the year-by-year and post-2014 impact of wildfire risk increases on municipal spreads in the primary and secondary market under a moderate emissions scenario (SSP2-4.5). 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, 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 10 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-39), and the weighted FWIs are calculated for each decennial period. We define ΔFire as the difference between the maturity-calendar-date-group-matched future FWI 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 county-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, it includes the standardized revenues from local sources, as well as its callability and sinkability status. For the primary market, we further control for the bond's log of face value and its sales method (negotiated or competitive). For the secondary market, we further control for the bond's age in years, its monthly trading volume divided by its face value, and the monthly standard deviation of its prices.

	(1)	(2)	(3)	
	Δ Fire	Δ Fire	Δ Fire	Δ Heat
Taxbase Risk × $\mathbb{I}$(Year = 2005)	0.196	-0.113	-0.872	32.182***
	(6.243)	(5.218)	(6.244)	(9.253)
Taxbase Risk × $\mathbb{I}$(Year = 2006)	6.402	0.177	4.411	33.152***
	(4.544)	(5.434)	(4.541)	(7.576)
Taxbase Risk × $\mathbb{I}$(Year = 2007)	5.037	1.751	3.260	21.157***
	(4.317)	(5.199)	(4.283)	(5.521)
Taxbase Risk × $\mathbb{I}$(Year = 2008)	5.243	8.626***	5.373	4.928
	(4.286)	(3.237)	(4.359)	(6.147)
Taxbase Risk × $\mathbb{I}$(Year = 2009)	0.339	-3.191	0.487	-0.380
	(2.589)	(4.103)	(2.665)	(5.556)
Taxbase Risk × $\mathbb{I}$(Year = 2010)	-1.497	-0.030	-1.802	8.886**
	(2.969)	(2.869)	(2.973)	(4.368)
Taxbase Risk × $\mathbb{I}$(Year = 2012)	10.104**	10.047**	9.504*	9.175**
	(4.776)	(4.705)	(4.838)	(3.841)
Taxbase Risk × $\mathbb{I}$(Year = 2013)	11.447***	11.267***	10.973***	9.401**
	(4.083)	(4.013)	(4.118)	(4.434)
Taxbase Risk × $\mathbb{I}$(Year = 2014)	12.011**	12.921***	12.342**	7.941*
	(5.319)	(4.801)	(5.310)	(4.506)
Taxbase Risk × $\mathbb{I}$(Year = 2015)	12.480***	8.598	11.532**	13.069**
	(4.712)	(5.440)	(4.666)	(5.102)
Taxbase Risk × $\mathbb{I}$(Year = 2016)	14.571**	9.723	13.155**	15.368***
	(5.858)	(5.912)	(5.892)	(5.192)
Taxbase Risk × $\mathbb{I}$(Year = 2017)	17.787***	16.720***	16.564***	13.781***
	(6.245)	(6.038)	(6.297)	(5.101)
Taxbase Risk × $\mathbb{I}$(Year = 2018)	17.554***	18.683***	16.177**	13.847***
	(6.440)	(5.998)	(6.497)	(5.040)
Taxbase Risk × $\mathbb{I}$(Year = 2019)	19.617***	20.715**	17.752**	18.338***
	(7.470)	(8.353)	(7.744)	(5.342)
Taxbase Risk × $\mathbb{I}$(Year = 2020)	21.644***	26.708***	19.789**	18.488***
	(7.965)	(8.803)	(8.301)	(5.492)
Observation	65,080	65,080	65,080	
R^2	0.479	0.526	0.481	
Taxbase Risk × $\mathbb{I}$(Year >= 2015)	9.119**	8.954**	8.002**	7.404**
	(3.883)	(3.948)	(3.915)	(2.974)
Observation	65,080	65,080	65,080	
R^2	0.477	0.522	0.478	
Mean Spread (basis points)	44.18	44.18	44.18	
State-by-Trade-Year-Month Fixed Effects	Y	Y	Y	
County-by-Maturity-Calendar-Date-Group Fixed Effects	Y	Y	Y	
Controls	Y	Y	Y	
Weights	Y	N	Y	
Cluster	County	County	County	

Table A19: Wildfire risk changes and municipal credit spreads in the secondary market - County bonds

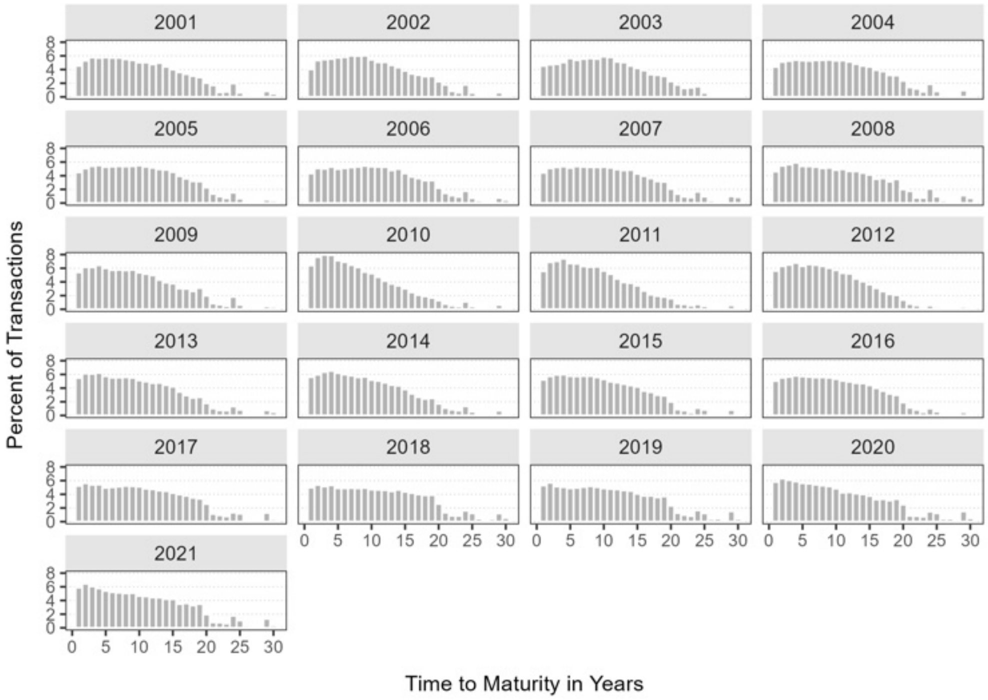
This table reports the year-by-year and post-2014 impact of wildfire risk increases on municipal spreads in the secondary market. Standard errors are reported in parentheses, clustered at the county level. *, **, and *** indicate the corresponding p-value less than 0.10, 0.05, and 0.01, respectively. The credit spread of a bond is defined as the difference between its yield to maturity, 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 10 years (e.g., Santa Barbara County bonds maturing in 2030-39), and the weighted FWIs are calculated for each decennial period. We define ΔFire as the difference between the maturity-calendar-date-group-matched future FWI and the historic level, which is standardized to a mean of zero and standard deviation of one. Similarly, we define ΔHeat as the difference between the maturity-calendar-date-group-matched population-weighted Heat Index and the historic level, which is standardized to a mean of zero and standard deviation of one. The regression includes the bond's county-by-maturity-calendar-date-group fixed effects and state-by-trade-year-month fixed effects. It also contains the log of the number of years before the maturity date interacted with the trade year indicator. In addition, we control for the monthly standard deviation of bond prices, as well as county-level unemployment rates and income per capita. Column (1) includes state-by-trade-year-month fixed effects, county-by-maturity-calendar-date-group fixed effects, and additional covariates. Column (2) weights each observation by the inverse of the count of county bonds within each state for a specific trade year. Column (3) further includes the changes in heat risk measured by the number of summer days with a seasonal average daily maximum heat index above 125.

	Mean	Std. Dev.	Observations
Fire Risk	4.58	5.88	25,924
Median value of owner-occupied housing units in 2017 USD (in ten thousands of dollars)	23.16	20.23	25,924
Mean household income in 2017 USD (in ten thousands of dollars)	7.31	2.62	25,924
Unemployment rate (%)	4.66	2.39	25,924

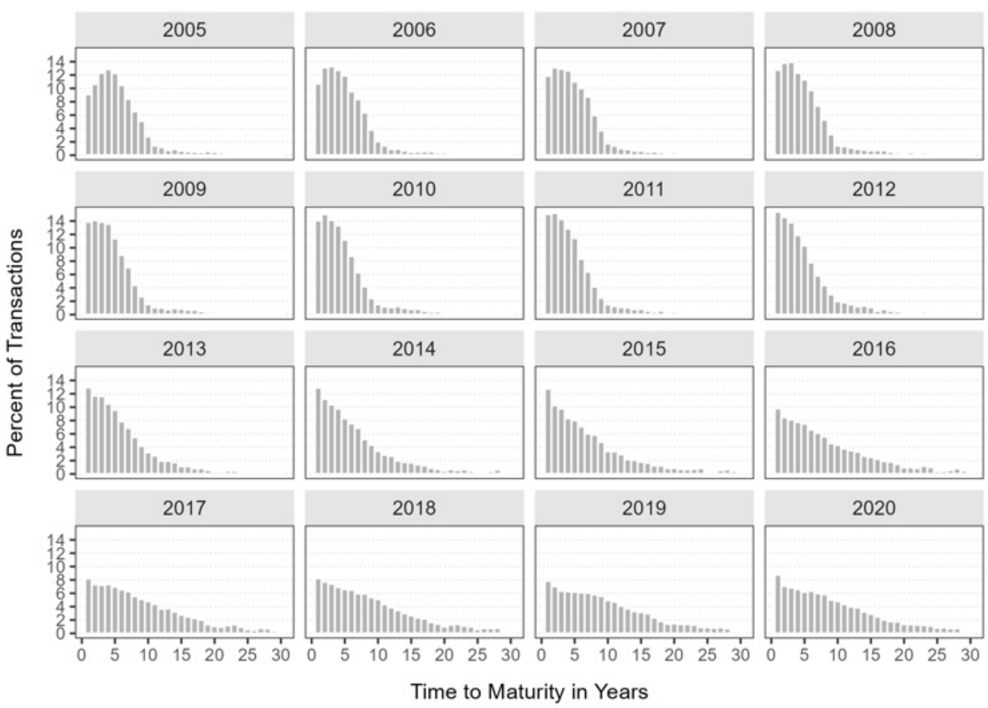
Table A20: Summary statistics for socioeconomic data

This table reports the summary statistics for the variables used in the sample. The sample comprises 25,924 district-year observations spanning from 2009 to 2021, with 2,698 school districts.

Appendix Figure



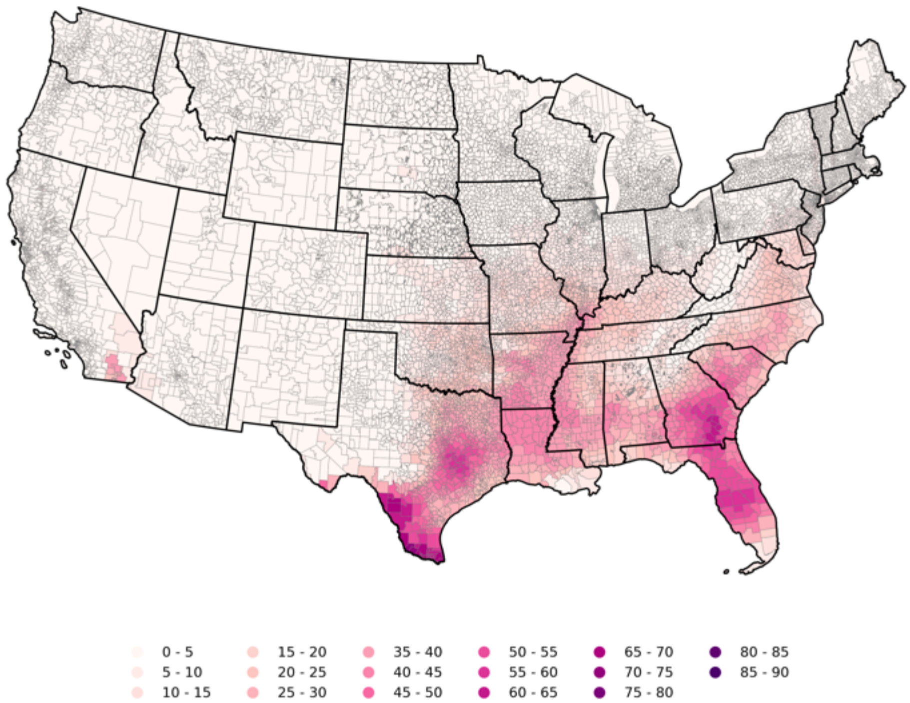
(a) Primary school district bond market



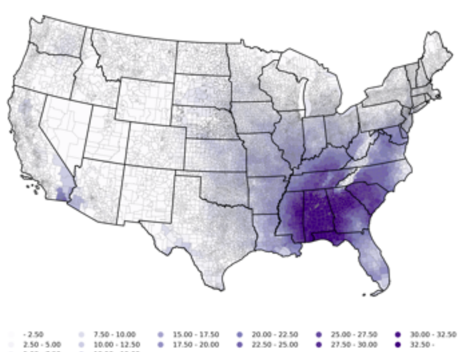
(b) Secondary school district bond market

Figure A1: Distribution of time to maturity by year

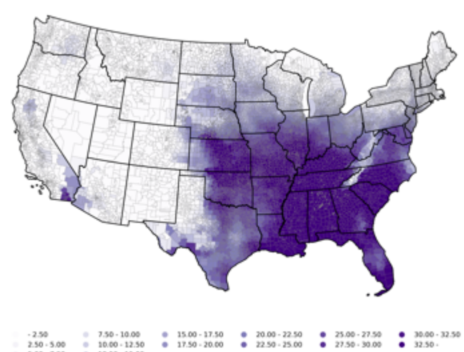
This figure displays the distribution of time-to-maturity (in years) for the school district bonds traded each year in our benchmark regression. Our primary and secondary school district bond data cover trades from 2001 to 2021 and issues from 2005 to 2020.



(a) Weighted HI (2000-2009)



(b) Difference (2020-2029 minus 2000-2009)



(c) Difference (2040-2049 minus 2000-2009)

Figure A2: Economic heat risks by school district under high emissions scenario (SSP5-8.5) Number of summer days with a seasonal average daily maximum Heat Index above 125

This figure maps school districts' weighted Heat Index (HI), based on Equation 15, along with their changes over time. The weights are determined by population size at the US census block level.

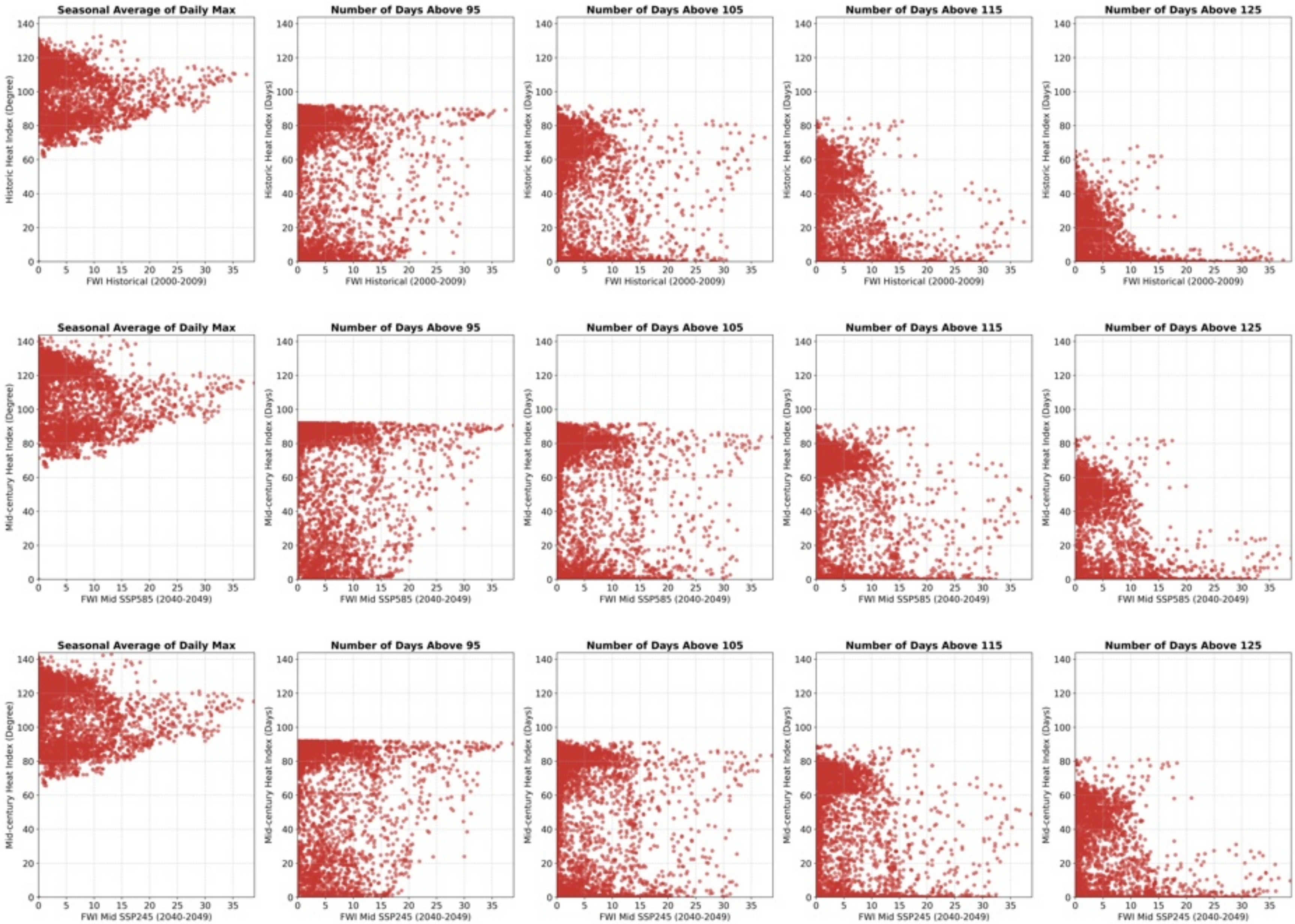


Figure A3: FWI versus Heat Index - School District

This figure displays a two-way scatter plot of housing unit-weighted FWI against five different population-weighted heat indices at the school district level in our benchmark regression for the historic and mid-century periods in the Northwestern (NW), Southwestern (SW), and Southern Great Plains (SGP) regions, as classified by USGCRP (2017).

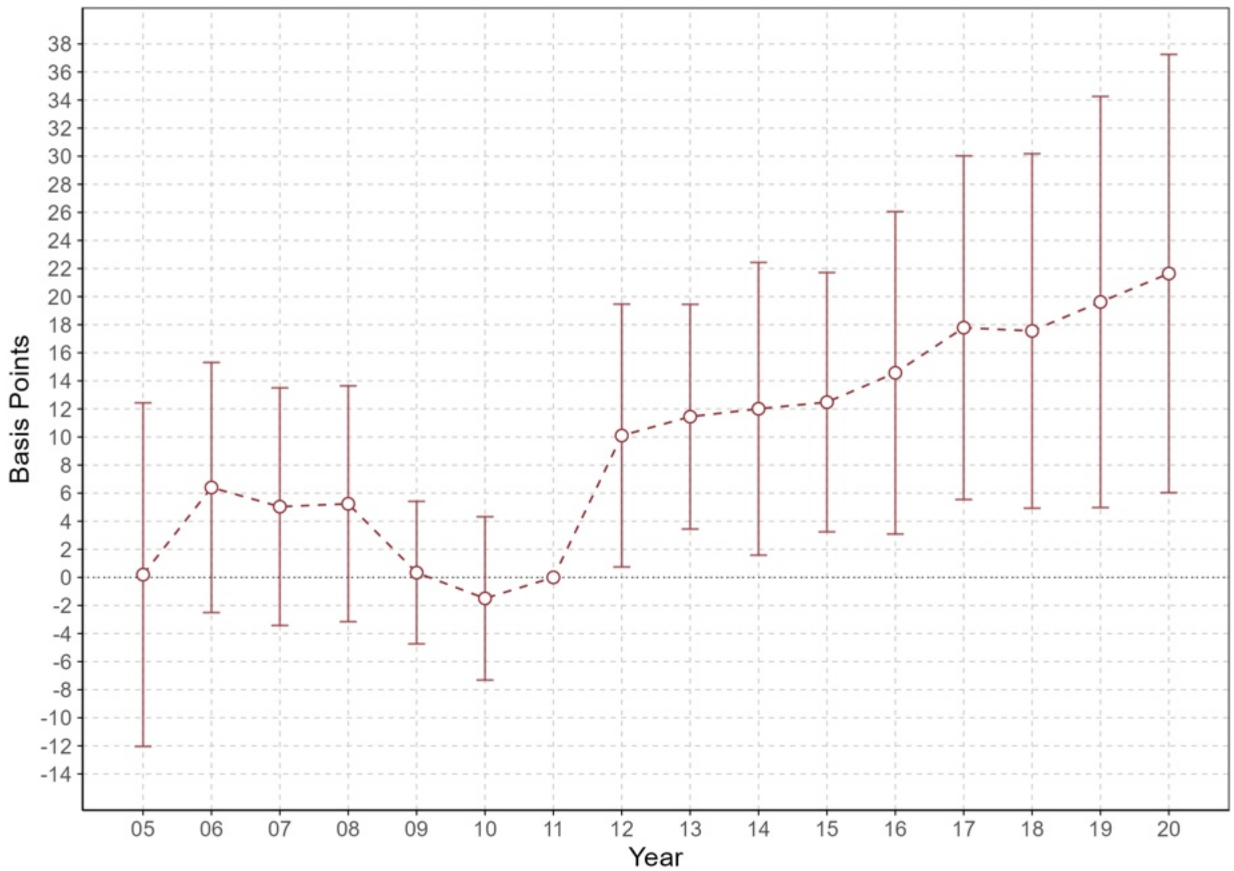


Figure A4: Wildfire risk changes and county credit spreads in the secondary market

This figure plots the year-by-year impact of wildfire risk increases on the credit spreads of county bonds in the secondary market, as described by Equation 5, with the baseline year set to 2011. 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 10 years (e.g., Santa Barbara County bonds maturing in 2030-39), and the weighted FWIs are calculated for each decennial period. We define ΔFire as the difference between the maturity-calendar-date-group-matched future FWI and the historic level, which is standardized to a mean of zero and standard deviation of one. The regression includes the bond's county-by-maturity-calendar-date-group fixed effects and state-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 monthly standard deviation of bond prices, as well as county-level unemployment rates and income per capita.

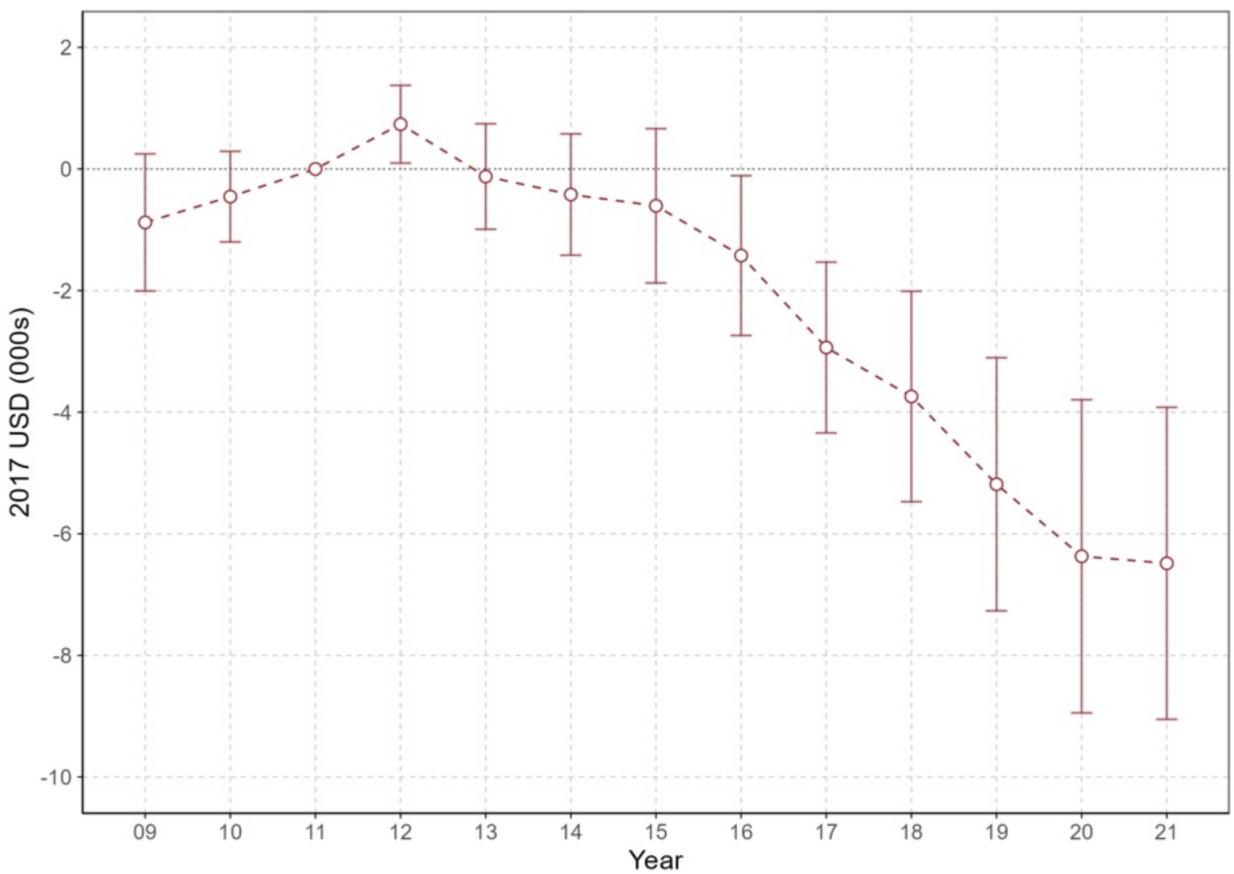


Figure A5: Association between future wildfire risk changes and housing values

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 16, 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 FWI values per district. The regression includes district fixed effects and state-by-year fixed effects. Additionally, we control for the logarithm of the mean household income and unemployment rate of each district.