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Pricing Climate Risks:
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Abstract

How do financial markets respond to anticipated climate-driven wildfire risk? Using high-resolution meteorological forecasts, land use data, and U.S. municipal bond spreads, we find that municipalities facing greater future wildfire exposure already incur higher borrowing costs: A one standard deviation increase in projected wildfire risk raises primary (secondary) market spreads by 14 (26) basis points - over 40% of the sample mean. Impacts are significantly 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 identifying the financial effects of evolving 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 from wildfire events, measured by the sum of insured and estimated uninsured losses, amounted to $30 billion (in 2024 USD), accounting for 26% of the total damages incurred from climate-related natural disasters in the US (NOAA, 2024). More recently, the catastrophic January 2025 wildfires in Los Angeles may turn out to be the costliest natural disaster in US history, with some estimates of insured property losses alone of $75 billion (Li and Yu, 2025). The rising property losses from growing wildfire risks (Boomhower, 2023) have also been associated with substantial fiscal costs (Baylis and Boomhower, 2023; Barrage, 2024) including for affected municipalities (Liao and Kousky, 2022). Even costlier are the estimated health impacts of wildfire smoke, which include over 15,000 excess deaths per year (Qiu et al., 2024). Importantly, the potential for wildfires is expected to continue rising in many parts of the US due to climate change (Brown et al., 2021).

Despite this growing evidence on their potential economic importance, wildfires have received comparatively little attention in the literature on the financial asset capitalization and social cost of climatic risks.[1] Recent industry reports also indicate continued skepticism as to whether climatic risks are reflected in municipal bond prices (see, e.g., NYSE: ICE 2022 and Stern and Smull 2024).

This paper presents what is to the best of our knowledge the first dedicated academic analysis of the capitalization of rising wildfire risks in US financial markets, specifically municipal bonds market. We exploit high-resolution meteorological predictions and granular variations in land use patterns to study whether asset prices reflect climate-induced wildfire risk changes. 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 (Goldsmith-Pinkham et al., 2023), is that wildfire risks are already present and changing in the near and

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

medium run, but differentially so across locations. Consequently, our analysis differs from cross-sectional comparisons across areas with different *levels* of present or long-term risk (e.g., Painter 2020) and is able to leverage variation in the wildfire risk across bonds issued *by the same municipality* to aid in the identification of the effects of climatic risk changes on asset prices. 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.

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. We focus on school district bonds due to their fine-scaled spatial variation in climatic risks, close link to local property markets,[2] and overall economic significance, with an estimated debt outstanding of $450 billion in 2022 (Ciccarone, 2023). This focus also aligns with recent work on the capitalization of sea level rise into municipal bonds (Goldsmith-Pinkham et al., 2023). Our bond-specific climate risk measure combines bond maturity structure with estimates of local historical and future physical wildfire risks 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. Our analysis permits the inclusion of a rich set of control variables including district-by-month fixed effects (e.g., Santa Barbara Unified School District in May 2024) and district-by-maturity-date-group fixed effects (e.g., Santa Barbara Unified School District bonds maturing between 2040 and 2044).

Our central finding is that future wildfire risks appear to be increasingly capitalized into US municipal bond markets. We observe both statistically and economically significant effects of future wildfire risk increases on bond spreads, with a one standard deviation increase in future wildfire exposure leading to a 14 (26)-basis point rise in school district primary (secondary) market bond spreads post-2014, which is equivalent to over 40% of the mean

[2] A majority of fixed income securities issued by school districts are general obligation bonds backed by property taxes, which establishes a direct link between local economic conditions and the ability to service debt.

spreads in the sample. The estimated impacts are robust to other estimation methods, expansion of spatial coverage to include the contiguous United States, and alternative wildfire measures. The results are also robust to excluding communities directly affected by wildfire events over our sample period and several controls for potentially confounding future heat risks. Delving into heterogeneity, we find that the capitalization of wildfire risks is more pronounced in districts with larger non-white population shares even after accounting for income. In the secondary 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.[3] In sum, our results indicate that anticipated future wildfire risk changes are already having economically significant impacts on financial markets, municipal borrowing costs, and vulnerable communities.

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

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

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).[4] To the best of our knowledge, this paper is the first to demonstrate the capitalization of anticipated climate-driven future wildfire risk changes into asset prices, and the first to utilize our research design with bond-specific risk measures within municipalities.

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), and mortgage-backed securities (Kahn et al., 2024).[5] Several recent studies have also used broad measures of historic natural disaster exposure that may include wildfires to demonstrate the overall impacts on financial market outcomes, including insurers' stock returns (Jung et al., 2023) and municipal bond returns (Auh et al., 2022).[6] 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, 2022), employment and income (Borgschulte et al., 2022; Walls and Wibbenmeyer, 2023; Roth Tran and Wilson, 2023), local business activities (Addoum et al., 2024a), crop yields (Behrer and Wang, 2024), student test scores (Wen and Burke, 2022),

[4] 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 (2023), have also used quantitative models to simulate the impacts of changing climate risks on sovereign bond markets.

[5] Berry-Stölzle and Hao (2025) examine the cross-sectional relation between present-day fire risks and city bond issue spreads.

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

and outdoor recreational activities (Gellman et al., 2023), in addition to well-established adverse health impacts (Wen et al., 2023; Qiu et al., 2024). The literature on consumer finance has recently quantified the direct costs of wildfire events on household balance sheets through consumer credit outcomes (McConnell et al., 2021), mortgage repayment (An et al., 2024; Biswas et al., 2023; Issler et al., 2024), and student loans (Cornaggia et al., 2023a). Finally, several studies on real estate markets have linked present-day wildfire risks to housing prices using spatially discontinuous hazard map updates (Ma et al., 2024; Garnache, 2023), historic wildfire events (McCoy and Walsh, 2018), and exposure to smoke plumes (Huang and Skidmore, 2024; Addoum et al., 2024b).

A fourth related strand is the emerging literature examining the fiscal perils associated with climate-related disasters. Most relevant, Liao and Kousky (2022) empirically find that wildfire events increase the probability of municipal budget deficits by 25 percentage points. Similarly, Jerch et al. (2023) document adverse impacts of 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,[7] there exists a distinct concern regarding the escalating fiscal burden resulting from wildfire risks (CBO, 2022; OMB, 2022). Recent studies have evaluated rising expenditures on specific programs directly related to fire events, such as wildfire suppression costs (Wibbenmeyer et al., 2019; Plantinga et al., 2022; Baylis and Boomhower, 2023) and Medicare spending (Miller et al., 2017). 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., 2024).

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

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 Economic wildfire risks

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

The US Global Change Research Program (USGCRP) divides the contiguous United States into seven regions to evaluate region-specific climate risks in its National Climate Assessment: Northwest (NW), Southwest (SW), Northern Great Plains (NGP), Southern Great Plains (SGP), Midwest (MW), Northeast (NE), and Southeast (SE) (USGCRP, 2017).[9] We restrict our sample to regions that have historically experienced KBDI values indicative of a high potential for wildfire events (> 400 in the period from 1995-2004, Liu et al. 2010),

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

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

specifically the NW, SW, and SGP regions. We provide a robustness check on our main regression by including other regions. To count the number of housing units exposed to different KBDI levels, we overlay 12 km resolution KBDI polygons with 2010 US census blocks, which represent the smallest geographical units used by the Census Bureau for housing data tabulation during its decennial census.

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

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

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

[10] Gannon and Steinberg (2021) confirm a positive correlation between fire occurrences and risk measures taking into account both meteorological conditions and land cover (globally and at a coarser resolution (1/4°) than Brown et al. (2021)).

Figure 1 maps the historic and mid-century weighted KBDI, along with their difference, in the Northwestern, Southwestern, and Southern Great Plains regions. In general, the Southwestern region exhibits high risk levels for both the historical and mid-century periods. But the Southern Great Plains area additionally stand out when considering the difference. We also consider an alternative measure of future wildfire potential in our robustness checks.[11] Importantly, as (1) captures only cross-sectionally varying risk, we transform the data to derive dynamically varying bond-level fire risks as described further below.

[FIGURE 1 HERE]

2.2 Bond trades in the secondary and primary markets

We use the Refinitiv Data Platform Application Programming Interface (RDP 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 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

[11] ANL (2023) calculates the seasonal average daily Fire Weather Index (FWI) — a wildfire risk index developed by the Canadian Forest Service — using Argonne's downscaled 12 km climate data under RCP 8.5. We find a strong correlation of 0.843 and 0.887 at the school district level in our sample between the difference in the weighted KBDI and the weighted FWI for the historic and mid-century periods, respectively. For details, see Appendix A.

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 C.

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 and clustering standard errors at the district level.

2.3 Maturity year-matched future wildfire risks

In contrast to sea level rise, wildfires pose risks both in the near and far future. Abatzoglou and Williams (2016) find that climate change has heightened fuel aridity across Western US forests from 1979 to 2015, correlating with increased wildfire occurrences. Additionally, Brown et al. (2021) observe a rising trend in annual mean KBDI over forested regions in the Southwestern and Northwestern US since 1982 as well. Both indicate a persistent drying trend, which could potentially exacerbate fire activities, even in the near future. Appendix Figure A1 displays the distribution of time-to-maturity in years for the bonds traded each year. The maturity calendar dates 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 5 years. For a bond b issued by a district d, let $m(b)$ denote the group to which its maturity calendar date belongs:

$$m(b) = \begin{cases} 0 & \text{if its maturity calendar date is before 2005,} \\ 1 & \text{if its maturity calendar date falls between 2005 and 2009,} \\ \cdots & \\ 9 & \text{if its maturity calendar date is after 2045.} \end{cases} \tag{2}$$

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

$$\begin{aligned} &\textsc{Weighted KBDI}_{d,m(b)} = \textsc{Weighted KBDI}_d(\text{history}) \\ &+ \left[\textsc{Weighted KBDI}_d(\text{mid-century}) - \textsc{Weighted KBDI}_d(\text{history}) \right] \times \frac{m(b)}{9}. \end{aligned} \tag{3}$$

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

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

We conduct a robustness check by varying the step size from 5 years to 4 and 6 years.

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 7.70 years, and the average increase in the weighted KBDI is 12.20. The sample comprises 405,621 bond-month trades spanning from 2005 to 2020, with 52,280 bonds issued by 1,641 school districts. Conditional on trading, the mean (median) number of bonds traded in a district-trade-year-month is 3.60 (2).

On the other hand, in the primary market, after winsorizing at the 1% level, the spreads vary from -53.06 to 145.23 basis points. The average time to maturity is 10.29 years, and the average increase in the weighted KBDI is 14.56. The sample comprises 150,013 issues spanning from 2001 to 2021 by 1,881 school districts. Conditional on issuance, the mean (median) number of bonds issued in a district-issue-year-month is 13.92 (14). 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 A2 presents the sample composition, breaking down each bond's trade by its issuing state and trading year. Bonds issued in California and Texas, or those traded in the later 2010s, are overrepresented. Thus, we provide a robustness check by weighting each bond by the inverse of the count of distinct bonds within each state for a specific year.

2.4 Historic wildfire perimeters

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

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

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

We filter events that occurred after 2005 to match municipal bond transaction data. We then define school districts impacted by large-scale wildfire events as those where more than 0.1% of housing units were affected for the first time during our sample period. We provide a robustness check by excluding all the transactions from school districts since they were first impacted by large-scale wildfire events, which amounts to 79,250 bond-month observations in the secondary market and 24,160 issues in the primary market.

2.5 Socioeconomic and municipal finance data

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

3 Empirical methods and results

3.1 Identification strategy

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

$$\textsc{Spread}_{b,d,c,t} = \lambda_{d,t} + \alpha_{d,m(b)} + \sum_{\substack{y=2001 \\ y\neq 2012}}^{2021} \mathbb{I}(\textsc{Year} = y) \; \left[\beta_y \Delta\textsc{Fire}_{d,m(b)} + \boldsymbol{\theta}_y' \mathbf{Z}_{b,d,c,t}\right] + \boldsymbol{\gamma}' \mathbf{X}_{b,d,c,t} + \varepsilon_{b,d,c,t}, \tag{6}$$

for the issuance of bond b, by school district d within county c and occurring in year-month t. We define Spread as the yield to maturity over its maturity-matched MMA municipal yield benchmark on the issue date for that bond.[12] Maturity calendar dates are grouped into intervals of 5 years, and wildfire risks are interpolated using a stepwise function with equal steps from the historic level (1995-2004) to the mid-century prediction (2045-2054). We define ΔFire as the difference between the maturity calendar date group-matched interpolated value and the historic level, which is now standardized to a mean of zero and standard deviation of one. The covariates in $\mathbf{Z}$ include the natural logarithm of the number of years before the maturity date (time to maturity in years) and insurance status to

[12] 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.

account for time-varying term premia and the evolution of municipal bond insurance value (Chun et al., 2019; Cornaggia et al., 2023b). Other covariates in $\mathbf{X}$ include each bond's natural logarithm of face value, its sales method (negotiated or competitive), as well as its callability and sinkability status. 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, as well as its callability and sinkability status.

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

In line with Goldsmith-Pinkham et al. (2023) and Acharya et al. (2022), we consider that awareness of future climate perils may have increased over time, following the release of the IPCC's fifth assessment report in 2014. 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 2012. To summarize impacts after 2014, we adopt the following specification:

$$\begin{aligned}\textsc{Spread}_{b,d,c,t} = \lambda_{d,t} + \alpha_{d,m(b)} + \beta\ \mathbb{I}(\textsc{Year} \geq 2015)\Delta\textsc{Fire}_{d,m(b)} \\ + \sum_{\substack{y=2001 \\ y\neq 2012}}^{2021} \mathbb{I}(\textsc{Year} = y)\boldsymbol{\theta}_y'\mathbf{Z}_{b,d,c,t} + \boldsymbol{\gamma}'\mathbf{X}_{b,d,c,t} + \varepsilon_{b,d,c,t},\end{aligned} \tag{7}$$

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

3.2 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 district-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 term structures 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 association between future wildfire risk changes and spreads in the baseline year (2012). This positive correlation can be partly attributed to the varying term structures 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. (2023b) 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 2014 becomes statistically indistinguishable from the baseline issue year. Similar to the findings in Goldsmith-Pinkham et al. (2023) and Acharya et al. (2022), we observe positive yearly coefficients around the release of the fifth IPCC report, which suggests that the difference in spreads among bonds with varying maturities begins to widen further in the mid-2010s compared to 2012. On average, a one standard-deviation increase in the weighted KBDI leads to a 13.6-basis point rise in school district bond spreads post-2014, which is about 40.5% of the average spreads in the sample.

Figure 2 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 2 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' credit-worthiness, we use the same empirical strategy as in Equation 6 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 between future wildfire risk changes and spreads in the baseline year, which can be attributed to varying term structures. 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 2005 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 KBDI leads to a 26.2-basis point rise in school district bond spreads post-2014, which is about 48.9% of the average spreads in the sample. Figure 3 visualizes the year-by-year estimates in column (3).

[Figure 3 Here]

3.4 Robustness

The results so far indicate that, even within the same municipality, bonds with larger embodied future wildfire risk increases command economically significantly higher yields. We conduct several robustness checks on our benchmark regression for both primary and secondary markets by adopting different estimation methods, expanding spatial coverage to include the contiguous US, using an alternative metric for wildfire risk, excluding communities directly impacted by wildfire events during our sample period, varying the step size for interpolating future wildfire risks within districts, and including heat risk 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 A2). Column (2) in Appendix Table A4 and Table A5 report the year-by-year and post-2014 impacts using equal weights. The post-2014 average impact of wildfire risk on spreads is higher, but 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 1,881 to 2,961 in the primary market whereas the number of bonds and districts in the secondary market increases from 52,280 to 68,780 and 1,641 to 2,458, respectively. Accordingly, the sample size increases from 148,461 to 205,694 in the primary market and from 361,194 to 469,381 in the secondary market, respectively. The associated summary statistics are provided in Appendix Table A3, 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. Columns (3) and (4) in Appendix Table A4 and Table A5 present the year-by-year and post-2014 impacts after including these instances. The former does not use equal weights, while the latter does.

The average impact post-2014 is higher, but the year-by-year patterns remain qualitatively similar to those observed in the benchmark regression.

Third, we expand the spatial coverage of our sample by including the Northeast, Southeast, Midwest, and Northern Great Plains regions. Appendix Table A6 and Table A7 replicate the main regression analysis with this expanded sample. While the year-by-year estimates exhibit similar patterns, the average impact post-2014 is smaller than the benchmark regression. The impact on credit spreads is smaller because the extended regions have meteorological conditions that are less prone to wildfires (Brown et al., 2021), meaning that a one standard deviation rise in wildfire risk represents a smaller increase than in our benchmark specification.

Fourth, we use the Fire Weather Index (FWI) calculated by ANL (2023) as an alternative metric for assessing wildfire risks. Specifically, we apply the same weighting methods outlined in Section 2 to the Summer average daily FWI, as the index reaches its peak during this season, to quantify the future wildfire risks for each district (see Appendix A for details). Panels (c) and (d) in Appendix Figure A2 map the spatial distribution of the weighted FWI across the contiguous US. The correlation between the weighted KBDI and the weighted FWI in our final sample is 0.84 and 0.89 in historic and mid-century periods, respectively. Appendix Table A8 and Table A9 replicate our main regression analysis using the weighted FWI. Both the year-by-year and post-2014 estimate exhibit the same pattern.

Fifth, we exclude observations starting from the year-month in which 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 A10 and Table A11 replicate the main regression analysis using the sample without directly affected communities. The year-by-year estimates exhibit similar patterns.

Sixth, we vary the step size used for interpolating future wildfire risks. Appendix Table A12 and Table A13 replicate the main regression analysis using step sizes of 4 and 6 years. The year-by-year patterns remain qualitatively similar.

Lastly, we include heat risks in addition to wildfire risks to see if our main result is driven by extreme heat events. Appendix Table A14 and Table A15 replicate our main regression analysis on the capitalization of wildfire risks using a Heat Index, which incorporates both temperature and humidity to evaluate how hot it feels to the human body (see Appendix B for details on quantifying economic heat risk). It is worth noting that the Keetch-Byram Drought Index (KBDI) is in general negatively correlated with the Heat Index because the KBDI is positively correlated with dry air, whereas the Heat Index increases with humidity.[13] The post-2014 average impacts of wildfire risk on spreads in primary and secondary markets are about 11 - 12 and 20 - 23 basis points when we control for the number of summer days with a seasonal average daily maximum heat index above 105 - 125 degrees.[14] However, the estimated impact attenuates when controlling for a 95 degree threshold or the seasonal average daily maximum Heat Index. This is because wildfire risk and these alternative heat measures are more positively correlated (see Appendix Figure A5).

3.5 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 local revenue sources, as might be expected if the estimated impacts reflect risks to future property values (Auh et al., 2022; Goldsmith-Pinkham et al., 2023). To implement the heterogeneity analysis, we categorize school districts into two groups: one with its own historical average ratio of local to total revenue greater than the national mean, and the other with a ratio below the national mean. We interact this indicator with wildfire risk changes in Equation 7.

The column (2) in Table 4 reports the post-2014 impact of wildfire risk changes on municipal spreads, interacted with the indicator of school districts heavily dependent on

[13] 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).

[14] 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.

local sources. The national average ratio of local to total school district revenue from 2005 through 2021 is about 40%. In the secondary market, about 50.6% of bond-month trades in our sample are issued by districts classified as locally dependent. A one-standard deviation increase in the weighted KBDI results in a 20.8-basis point increase in municipal spreads post-2014 for districts where less than 40% of revenues are from local sources. Locally dependent school districts face a 34.0-basis point increase in credit spreads in response to a one-standard deviation in the weighted KBDI. On the other hand, in the primary market, about 46.3% of bonds in our sample are issued by locally dependent districts. These do not, however, command economically nor statistically higher initial yield increases from future wildfire risks.

[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 categorize districts into two groups: one with its own historical ratio of nonwhite population greater than 35%, and the other with a percentage less than 35%. The white alone population account for about 70% and 60% in the 2010 and 2020 US Census, respectively. We choose the midpoint as a threshold and about 30.3% and 39.7% of trades in our sample are issued by districts classified as high minority share in the primary and secondary market, respectively. We further control for district-wide income levels to mitigate their potential confounding effects on distributional outcomes. The nationwide average median household income by school district from 2009 to 2021 is about $58,107 (in 2017 USD). We classify school districts as "High Income" if their own average median household income is above $58,107 (in 2017 USD). Our finding in column (3) of Table 4 shows that a one-standard deviation increase in the weighted KBDI leads to an 9.9 and 21.2-basis point increases in credit spreads post-2014 for districts where less than 35% of the population identifies as non-white in the primary and secondary market, respectively. School districts with higher minority shares experience a 16.9 and 34.7-basis point increases in municipal spreads following a one-standard deviation increase in the weighted KBDI in the primary and secondary market, respectively, which remain robust even after controlling for income levels. Taken together, these results suggest that both fiscal structure and racial composition may be relevant to identifying vulnerable communities.

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

4 Conclusion

This paper examines whether financial markets are responding to projections of climate-driven wildfire risk changes. We ask this question in the context of the US municipal bond market and wildfire risks, where policy makers have shown increasing concern,[15] but little is known about their impacts empirically. Our main result is that increases in projected wildfire risks over the next 30 years are already associated with economically significant increases in municipal borrowing costs. The emergence of this association in the mid-2010s coincides with increased capitalization of other climatic risks into US municipal bond markets, including sea level rise (Goldsmith-Pinkham et al., 2023) and heat stress (Acharya et al., 2022), suggesting that these trends are not limited to a specific type of climatic risk. At the same time, our results also demonstrate the importance of studying different climate risk factors individually, as prior work considering wildfires only as part of general climate risk indices has often failed

[15] "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.

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 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 lower-income and 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 policy-makers and scholars are exploring risk-sharing financial innovations (e.g., Mallucci, 2022; Phan and Schwartzman, 2023). Whether and which risk-sharing innovations could aid US municipalities facing growing climate risks is thus an important area for future research.

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Panel A: Steps to Cleaning Municipal Bond 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
Merge with MMA benchmark yield	724,112
Merge with climate risks and other socioeconomic data	691,466
Drop issues for which the sales method is not available	595,377
Select bonds issued in the NW, SW, and SGP regions	208,223
Select bonds issued in counties with more than one school district	150,013

Secondary Market	# of Trades
Full MSRB sample	145,451,842
Select federally tax-exempt school district bonds	23,062,421
Drop pre-refunded bonds	13,517,019
Remove clerical errors and select bonds traded at least 10 times	12,248,508
Drop bonds with a time to maturity greater than 30 years	12,188,308
Drop trades during the last year before maturity	11,355,720
Drop trades during the first three months after the issuance	8,161,606
Construct a monthly panel and merge with MMA benchmark yield	1,269,703
Merge with climate risks and other socioeconomic data	1,140,972
Select bonds issued in the NW, SW, and SGP regions	531,640
Select bonds issued in counties with more than one school district	406,621

Panel B: Summary Statistics

Primary Market	Mean	Std. Dev.	Observations
Fire Risk Change	14.56	16.88	150,013
Yield-To-Maturity	2.82	1.29	150,013
Spread (basis points)	33.64	43.23	150,013
Time to Maturity (years)	10.29	6.51	150,013
Face Issued Total (Millions USD)	2.03	7.44	150,013
$\mathbb{I}\{\text{Insured}\}$	0.31	0.46	150,013
$\mathbb{I}\{\text{Callable}\}$	0.51	0.50	150,013
$\mathbb{I}\{\text{Sinkable}\}$	0.08	0.27	150,013
$\mathbb{I}\{\text{Competitive}\}$	0.40	0.49	150,013

Secondary Market	Mean	Std. Dev.	Observations
Fire Risk Change	12.20	15.59	406,621
Yield-To-Maturity	2.38	1.22	406,621
Spread (basis points)	53.66	62.28	406,621
Time to Maturity (years)	7.70	6.22	406,621
Bond Age (years)	3.06	2.74	406,621
Monthly Trading Volume (Thousands USD)	599.84	2,659.69	406,621
Monthly Turnover	0.23	0.55	406,621
Monthly Standard Deviation of Price	0.62	0.66	406,621
$\mathbb{I}\{\text{Insured}\}$	0.35	0.48	406,621
$\mathbb{I}\{\text{Callable}\}$	0.42	0.49	406,621
$\mathbb{I}\{\text{Sinkable}\}$	0.09	0.28	406,621

Table 1: Sample construction

This table summarizes the sample construction for the secondary and primary municipal 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 406,621 bond-month trades spanning from 2005 to 2020, with 52,280 bonds issued by 1,641 school districts. The primary market sample consists of 150,013 bonds issued by 1,881 school districts, spanning from 2001 to 2021. Panel B reports the summary statistics for the variables used in the final sample. Fire Risk Change is the difference between the maturity-calendar-date-group-matched interpolated weighted KBDI and the historical weighted KBDI within a district. Yield-to-Maturity is an annual interest rate that equates the present value of cash flow payments received from a bond with the monthly mean of its daily fundamental prices 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. $\mathbb{I}\{\text{Insured}\}$, $\mathbb{I}\{\text{Callable}\}$, and $\mathbb{I}\{\text{Sinkable}\}$ denote the insurance, callability, and sinkability status, respectively. $\mathbb{I}\{\text{Competitive}\}$ denotes the sales method by which the bond is traded, either through negotiation or competitive bidding.

	1	2	3
Δ Fire	28.26***		
	(3.174)		
Δ Fire × $\mathbb{I}$(Year = 2001)	-23.59***	-41.19***	7.277*
	(3.524)	(4.077)	(3.773)
Δ Fire × $\mathbb{I}$(Year = 2002)	-20.75***	-46.69***	1.246
	(3.366)	(4.110)	(4.539)
Δ Fire × $\mathbb{I}$(Year = 2003)	-27.69***	-50.61***	-2.402
	(5.277)	(5.386)	(4.066)
Δ Fire × $\mathbb{I}$(Year = 2004)	-23.23***	-41.57***	1.449
	(3.300)	(4.218)	(3.458)
Δ Fire × $\mathbb{I}$(Year = 2005)	-18.28***	-30.23***	4.286
	(3.242)	(3.705)	(3.201)
Δ Fire × $\mathbb{I}$(Year = 2006)	-22.47***	-30.38***	4.625*
	(3.115)	(2.693)	(2.788)
Δ Fire × $\mathbb{I}$(Year = 2007)	-20.97***	-25.26***	6.359*
	(3.302)	(3.516)	(3.365)
Δ Fire × $\mathbb{I}$(Year = 2008)	-33.34***	-34.60***	5.305
	(3.779)	(3.853)	(3.482)
Δ Fire × $\mathbb{I}$(Year = 2009)	-27.92***	-37.14***	-14.05***
	(3.911)	(4.172)	(4.012)
Δ Fire × $\mathbb{I}$(Year = 2010)	-17.19***	-15.07***	-0.924
	(3.529)	(3.631)	(3.480)
Δ Fire × $\mathbb{I}$(Year = 2011)	-21.91***	-21.13***	-4.003
	(3.994)	(4.309)	(3.740)
Δ Fire × $\mathbb{I}$(Year = 2013)	-5.964	2.178	2.599
	(4.118)	(2.904)	(2.784)
Δ Fire × $\mathbb{I}$(Year = 2014)	5.385	11.03***	3.630
	(3.557)	(2.717)	(2.563)
Δ Fire × $\mathbb{I}$(Year = 2015)	10.46***	17.44***	12.28***
	(4.024)	(2.633)	(2.598)
Δ Fire × $\mathbb{I}$(Year = 2016)	23.72***	31.76***	13.37***
	(3.978)	(2.871)	(3.131)
Δ Fire × $\mathbb{I}$(Year = 2017)	24.38***	32.09***	11.01***
	(4.347)	(2.784)	(3.076)
Δ Fire × $\mathbb{I}$(Year = 2018)	23.57***	42.44***	18.43***
	(4.732)	(2.942)	(2.866)
Δ Fire × $\mathbb{I}$(Year = 2019)	45.22***	61.20***	24.50***
	(5.992)	(3.810)	(3.284)
Δ Fire × $\mathbb{I}$(Year = 2020)	35.03***	56.24***	26.16***
	(6.207)	(3.572)	(2.938)
Δ Fire × $\mathbb{I}$(Year = 2021)	32.82***	50.78***	29.44***
	(4.276)	(3.119)	(3.781)
R^2	0.714	0.869	0.910
Δ Fire	11.15***		
	(1.130)		
Δ Fire × $\mathbb{I}$(Year >= 2015)	43.29***	47.31***	13.63***
	(3.463)	(2.053)	(1.336)
R^2	0.707	0.860	0.909
District-by-Issue-Year-Month Fixed Effects	Y	Y	Y
District-by-Maturity-Calendar-Date-Group Fixed Effects	N	Y	Y
Controls	N	N	Y
Observations	149,530	148,461	148,461

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 6 and Equation 7. Standard errors are reported in parentheses, clustered at the county level. *, **, and *** indicate the corresponding p-value less than 0.10, 0.05, and 0.01, respectively. The credit spread of a bond is defined as the difference between its yield to maturity, 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 5 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-35), and wildfire potentials are interpolated using a stepwise function from the historic level (1995-2004) to the mid-century prediction (2045-2054). We define ΔFire as the difference between the maturity-calendar-date-group-matched interpolated value and the historic level, which is standardized to a mean of zero and standard deviation of one. The regression includes the bond's district-by-maturity-calendar-date-group fixed effects and district-by-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), as well as its callability and sinkability status.

	1	2	3
Δ Fire	47.33***		
	(3.503)		
Δ Fire $\times$ $\mathbb{I}$(Year = 2005)	-20.74***	-32.27***	8.588
	(4.239)	(8.870)	(8.404)
Δ Fire $\times$ $\mathbb{I}$(Year = 2006)	-29.93***	-47.76***	1.982
	(4.244)	(7.177)	(7.575)
Δ Fire $\times$ $\mathbb{I}$(Year = 2007)	-26.98***	-39.89***	3.594
	(3.764)	(7.301)	(5.138)
Δ Fire $\times$ $\mathbb{I}$(Year = 2008)	-37.08***	-48.34***	-0.224
	(10.95)	(12.80)	(6.426)
Δ Fire $\times$ $\mathbb{I}$(Year = 2009)	-22.29*	-30.56**	-6.011
	(12.13)	(15.12)	(13.53)
Δ Fire $\times$ $\mathbb{I}$(Year = 2010)	-12.11	-20.41**	-3.541
	(8.359)	(9.788)	(8.322)
Δ Fire $\times$ $\mathbb{I}$(Year = 2011)	-11.84*	-18.18**	-5.663
	(6.247)	(8.200)	(7.859)
Δ Fire $\times$ $\mathbb{I}$(Year = 2013)	-10.56**	-7.608***	-7.714***
	(4.090)	(2.373)	(2.271)
Δ Fire $\times$ $\mathbb{I}$(Year = 2014)	-6.987	-2.125	3.197
	(5.102)	(3.878)	(3.230)
Δ Fire $\times$ $\mathbb{I}$(Year = 2015)	-4.616	6.971	18.45***
	(4.129)	(5.371)	(4.235)
Δ Fire $\times$ $\mathbb{I}$(Year = 2016)	9.633**	24.26***	21.70***
	(4.113)	(6.415)	(4.890)
Δ Fire $\times$ $\mathbb{I}$(Year = 2017)	7.469**	24.47***	21.90***
	(3.781)	(6.523)	(4.833)
Δ Fire $\times$ $\mathbb{I}$(Year = 2018)	6.740*	29.42***	23.70***
	(3.789)	(6.951)	(4.624)
Δ Fire $\times$ $\mathbb{I}$(Year = 2019)	25.41***	56.42***	33.21***
	(5.286)	(8.859)	(5.173)
Δ Fire $\times$ $\mathbb{I}$(Year = 2020)	28.68***	62.43***	33.63***
	(6.538)	(10.16)	(6.074)
R^2	0.525	0.657	0.760
Δ Fire	32.14***		
	(3.725)		
Δ Fire $\times$ $\mathbb{I}$(Year >= 2015)	31.08***	39.19***	26.21***
	(7.469)	(5.694)	(5.232)
R^2	0.523	0.653	0.760
District-by-Trade-Year-Month Fixed Effects	Y	Y	Y
District-by-Maturity-Calendar-Date-Group Fixed Effects	N	Y	Y
Controls	N	N	Y
Observations	362,876	361,967	361,194

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 6 and Equation 7. Standard errors are reported in parentheses, clustered at the county level. *, **, and *** indicate the corresponding p-value less than 0.10, 0.05, and 0.01, respectively. The credit spread of a bond is defined as the difference between its yield to maturity, calculated from the monthly mean of its fundamental daily prices, and its maturity-matched Municipal Market Analytics (MMA) yield benchmarks in basis points, based on the last trade date each year-month. Maturity calendar dates are grouped into intervals of 5 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-35), and wildfire potentials are interpolated using a stepwise function from the historic level (1995-2004) to the mid-century prediction (2045-2054). We define ΔFire as the difference between the maturity-calendar-date-group-matched interpolated value and the historic level, which is standardized to a mean of zero and standard deviation of one. The regression includes the bond's district-by-maturity-calendar-date-group fixed effects and district-by-trade-year-month fixed effects. It also contains the log of the number of years before the maturity date and insurance status interacted with the trade year indicator. In addition, we control for the bond's age in years, its monthly trading volume divided by its face value, the monthly standard deviation of its prices, as well as its callability and sinkability status.

Panel A: Primary Market

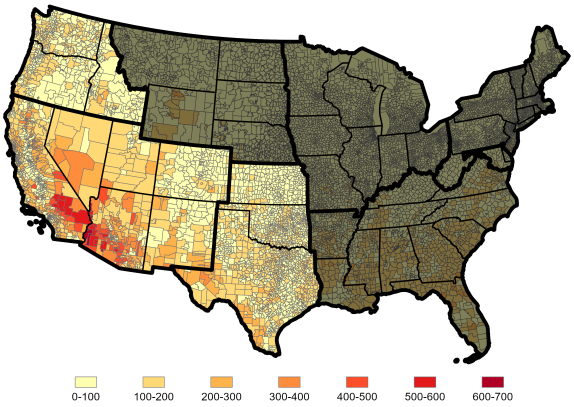
	1	2	3
Δ Fire × $\mathbb{I}$(Year >= 2015)	13.63***	13.32***	9.851***
	(1.336)	(1.802)	(2.055)
Δ Fire × $\mathbb{I}$(Year >= 2015) × $\mathbb{I}$(Locally Dependent)		0.731	
		(2.356)	
Δ Fire × $\mathbb{I}$(Year >= 2015) × $\mathbb{I}$(With a Racial Minority Population)			7.083***
			(2.456)
Δ Fire × $\mathbb{I}$(Year >= 2015) × $\mathbb{I}$(High Income)			3.183
			(2.176)
R^2	0.909	0.909	0.909
District-by-Issue-Year-Month Fixed Effects	Y	Y	Y
District-by-Maturity-Calendar-Date-Group Fixed Effects	Y	Y	Y
Controls	Y	Y	Y
Observations	148,461	148,461	148,461

Panel B: Secondary Market

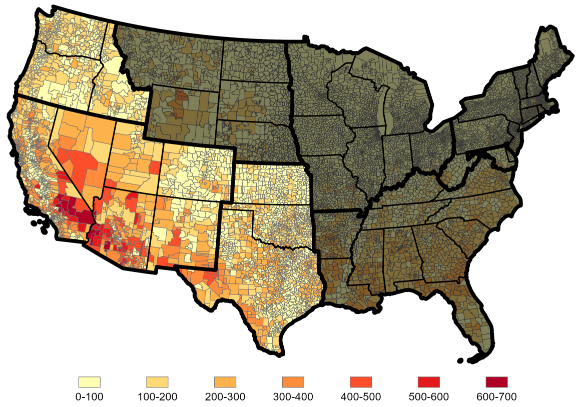
	1	2	3
Δ Fire × $\mathbb{I}$(Year >= 2015)	26.21***	20.82***	21.15***
	(5.232)	(5.388)	(5.536)
Δ Fire × $\mathbb{I}$(Year >= 2015) × $\mathbb{I}$(Locally Dependent)		13.14**	
		(6.604)	
Δ Fire × $\mathbb{I}$(Year >= 2015) × $\mathbb{I}$(With a Racial Minority Population)			13.59**
			(5.424)
Δ Fire × $\mathbb{I}$(Year >= 2015) × $\mathbb{I}$(High Income)			-0.267
			(6.212)
R^2	0.760	0.760	0.760
District-by-Trade-Year-Month Fixed Effects	Y	Y	Y
District-by-Maturity-Calendar-Date-Group Fixed Effects	Y	Y	Y
Controls	Y	Y	Y
Observations	361,194	361,194	361,194

Table 4: Effect of wildfire risk changes on municipal credit spreads in the secondary market - Heterogeneity analyses

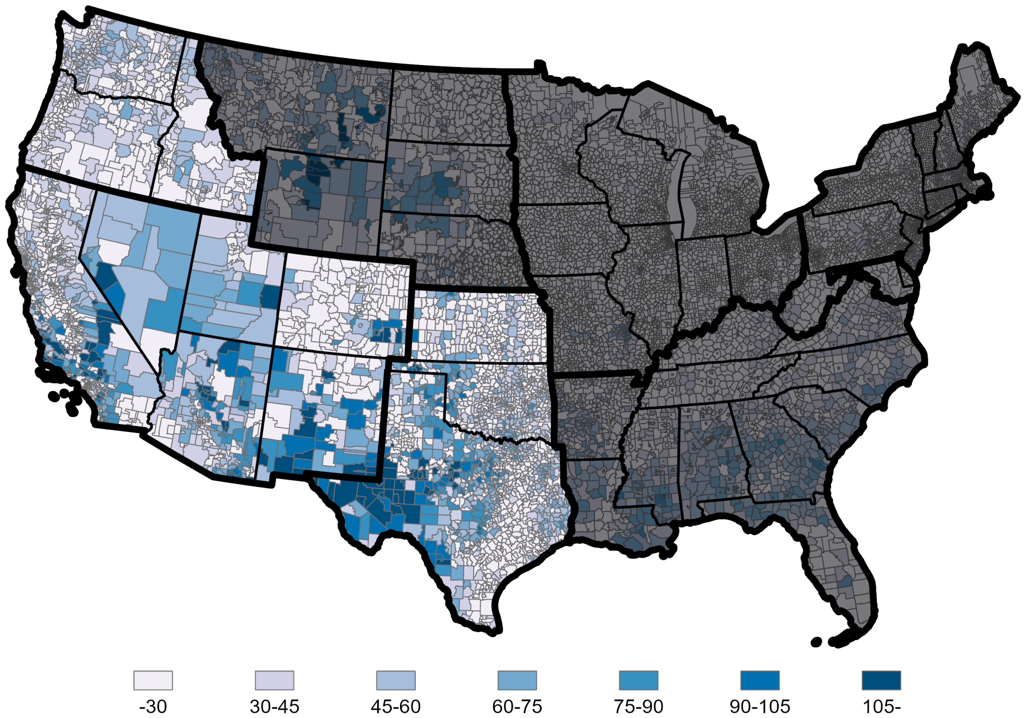
This table reports the heterogeneous impacts of wildfire risk increases on municipal spreads in the primary and secondary market post-2014, as outlined in Equation 7 in which fire risk changes are further interacted with the indicator for heterogeneity. Standard errors are reported in parentheses, clustered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



(a) Historic weighted KBDI (1995-2004)



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



(c) Difference (Mid-century minus Historic)

Figure 1: Wildfire exposure by school district

This figure maps school districts' historic and mid-century weighted Keetch-Byram Drought Index (KBDI), based on Equation 8, along with their differences in the Northwestern (NW), Southwestern (SW), and Southern Great Plains (SGP) regions, as classified by USGCRP (2017). We restrict the sample to these regions because their average daily unweighted KBDI values exceed 400 in September, October, and November during the historic period from 1995 to 2004 (Brown et al., 2021). This threshold generally indicates late summer or early fall weather conditions with a high potential for wildfire events (Liu et al., 2010). We provide a robustness check on our main regression by including other regions in the appendix. 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.

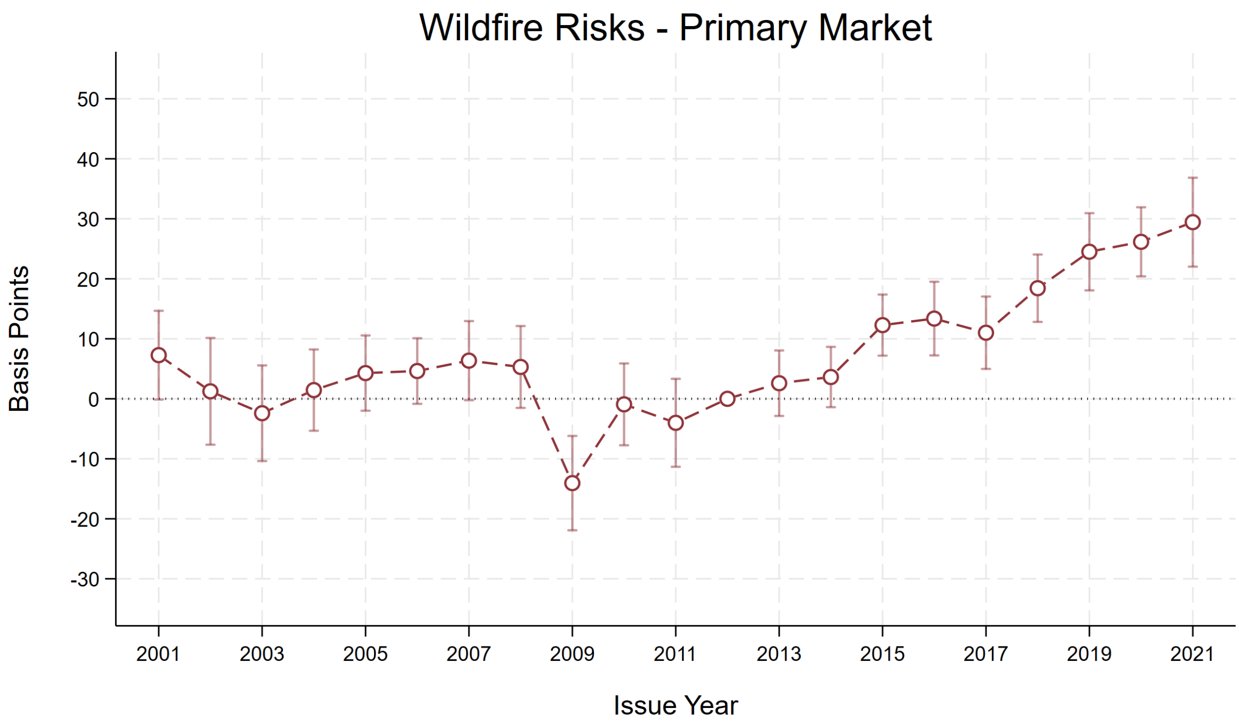


Figure 2: Effect of wildfire risk changes on municipal credit spreads in the primary market

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 6, with the baseline year set to 2012. 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 5 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-35), and wildfire potentials are interpolated using a stepwise function from the historic level (1995-2004) to the mid-century prediction (2045-2054). We define ΔFire as the difference between the maturity-calendar-date-group-matched interpolated value and the historic level, which is standardized to a mean of zero and standard deviation of one. The regression includes the bond's district-by-maturity-calendar-date-group fixed effects and district-by-trade-year-month fixed effects. It also contains the log of the number of years before the maturity date and insurance status interacted with the trade year indicator. In addition, we control for the bond's log of face value, its sales method (negotiated or competitive), as well as its callability and sinkability status.

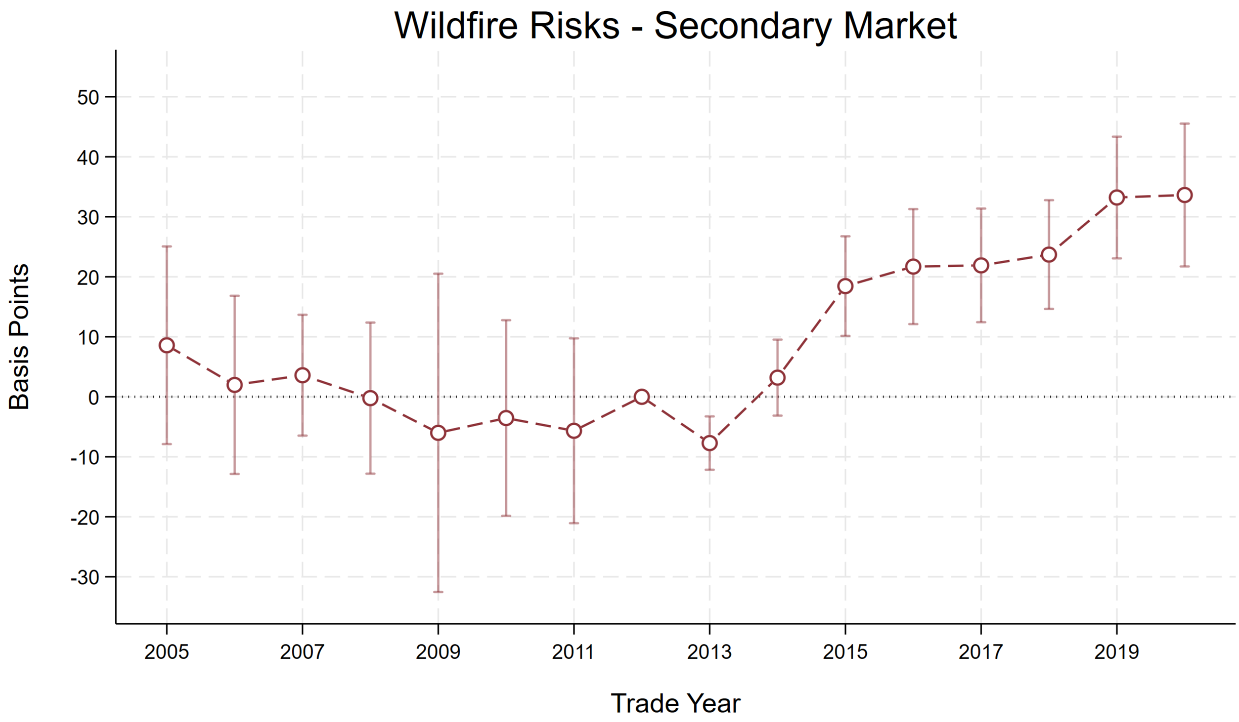


Figure 3: Effect of wildfire risk changes on municipal credit spreads in the secondary market

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 6, with the baseline year set to 2012. The vertical lines denote the 95% confidence intervals, with standard errors clustered at the county level. The credit spread of a bond is defined as the difference between its yield to maturity, calculated from the monthly mean of its fundamental daily prices, and its maturity-matched Municipal Market Analytics (MMA) yield benchmarks in basis points, based on the last trade date each year-month. Maturity calendar dates are grouped into intervals of 5 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-35), and wildfire potentials are interpolated using a stepwise function from the historic level (1995-2004) to the mid-century prediction (2045-2054). We define ΔFire as the difference between the maturity-calendar-date-group-matched interpolated value and the historic level, which is standardized to a mean of zero and standard deviation of one. The regression includes the bond's district-by-maturity-calendar-date-group fixed effects and district-by-trade-year-month fixed effects. It also contains the log of the number of years before the maturity date and insurance status interacted with the trade year indicator. In addition, we control for the bond's age in years, its monthly trading volume divided by its face value, the monthly standard deviation of its prices, as well as its callability and sinkability status.

Online Appendix for

Pricing Climate Risks: Evidence from Wildfires and Municipal Bonds

A An Alternative Measure of Economic Wildfire Risks

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

As a robustness check, we use their summer average daily FWI to measure the wildfire potential of each school district, as this index reaches its peak during summer.[16] Given the consistency in spatial resolution, prediction time scale, and emissions scenario between KBDI and FWI, we apply the same method in Section 2 to compute the economic fire risks.

[Figure A2 Here]

Figure A2 maps the spatial distribution of the weighted KBDI, the weighted summer FWI, and their correlation coefficients across school districts in the contiguous United States. In the mid-century, the Northwest (NW), Southwest (SW), and Southern Great Plains (SGP) regions exhibit elevated wildfire potentials in both metrics. The Northern Great Plains (NGP) show high fire risks for FWI, while the Southeast (SE) regions display high risks for

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

KBDI. The correlation coefficient between KBDI and summer FWI is 0.843 and 0.887 for the historic and mid-century periods, respectively.

B Economic Heat Risks

ANL (2023) computes the extended Heat Index (HI), developed by Lu and Romps (2022), across the contiguous US at a spatial resolution of 12 km for both historic (1995-2004) and mid-century (2045-2054) periods. It uses temperature and relative humidity to assess how hot it feels to the human body, based on the model of human thermoregulation by Steadman (1979). Low humidity helps sweat evaporate faster, making high temperatures feel less extreme, while high humidity slows sweat evaporation, making moderate temperatures feel much hotter.

[Figure A3 Here]

Figure A3 displays the Heat Index chart from the National Weather Service, based on the extended Heat Index developed by Lu and Romps (2022). It shows how the weather feels to the human body based on temperature and relative humidity. A Heat Index greater than 105 indicates that sunstroke, heat cramps, or heat exhaustion are likely, and heat stroke is possible with prolonged exposure and/or physical activity.[17] Using Argonne's climate data under the high-emissions scenario (RCP 8.5) and across three different climate models mentioned above, ANL (2023) generates the ensemble mean of the summer daily maximum Heat Index. They then calculate 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 degrees Fahrenheit.

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

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 both historic and mid-century periods, using the population as weights: for $p \in \{\text{historic}, \text{mid-century}\}$,

$$\text{Weighted HI}_d(p) = \sum_{i=1}^{N_d} \left[\frac{\text{Population}_i}{\sum_{j=1}^{N_d} \text{Population}_j} \times \text{HI}_i(p) \right]. \tag{8}$$

Figure A4 maps the historic and mid-century weighted HI in the contiguous United States. In general, the Southern Great Plains and Southeast regions exhibit high risk levels for both the historical and mid-century periods, along with parts of the Southwestern and Midwest regions.

[Figure A4 Here]

C Name Matching

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

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

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

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

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

   (c) Exclude 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.[18] Enter the information identified above and match accordingly.

3. Check the manually matched outcomes and categorize any unmatched cases as follows:

   (a) Multiple districts per issuance (e.g., AUBURN CALIF UN SCH DIST)

   (b) No official statement (e.g., BAY AREA SCH FOR INDPT STUDY INC CALIF)

   (c) No issuer name on EMMA (e.g., ARKANSAS ST DEV FIN AUTH CAP IMPT REV)

   (d) College (e.g., ALABAMA ST UNIV CTFS PARTN)

   (e) State, county, or city (e.g., PELHAM ALA)

   (f) Technical/vocational (e.g., EAST VY ARIZ INST OF TECHNOLOGY DIST NO 401)

   (g) Charter (e.g., CALIFORNIA MUN FIN AUTH CHARTER SCH LEASE REV)

   (h) Others (e.g., ARIZONA INDL DEV AUTH REV)

4. Drop the unmatched cases.

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

D 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 balanced panel by merging this dataset together with our risk map using the Local Education Agency Identity (LEAID). Appendix Table A16 provides summary statistics.

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

$$Y_{d,c,t} = \lambda_{c,t} + \alpha_d + \sum_{\substack{y=2009 \\ y\neq 2011}}^{2021} \beta_y \Delta \textsc{Fire}_d \mathbb{I}(\textsc{Year} = y) + \boldsymbol{\gamma}' \mathbf{X}_{d,t} + \varepsilon_{d,c,t}, \tag{9}$$

for school district d within county c and in year t. Our outcome variable is the median value of owner-occupied housing units.[19] We exclude school districts that span across more than one county to control for time-varying economic conditions at the county level ($\lambda_{c,t}$). Additionally, we exclude all observations starting from the year in which they were first impacted by large-scale 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.

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

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

Figure A6 plots the year-by-year association of future wildfire risk changes with median value of owner-occupied housing units, which exhibits a persistent negative correlation since 2017. A one standard-deviation in the weighted KBDI is associated with an approximately \$6,000 (in 2017 USD) decrease in the median value of owner-occupied housing units in 2021 relative to 2011, which is equivalent to 2.3% of the average median value of owner-occupied housing units across all school districts. We also run a before-and-after analysis for the year 2015, similar to the equation (7). The corresponding coefficients have the same sign as the year-by-year estimates and are statistically significant at the 5% level.

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

Table A1: National Climate Assessment (NCA) regions of the contiguous United States (CONUS)

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

Panel A: By State

Primary Market		
	# of Issues	Percent
Arizona	7,044	4.70
California	65,095	43.39
Colorado	3,003	2.00
Idaho	1,036	0.69
Kansas	3,034	2.02
New Mexico	3,150	2.10
Oklahoma	5,135	3.42
Oregon	2,494	1.66
Texas	50,420	33.61
Utah	1,804	1.20
Washington	7,798	5.20
Total	150,013	100

Secondary Market		
	# of Trades	Percent
Arizona	30,319	7.46
California	200,481	49.3
Colorado	10,313	2.54
Idaho	2,006	0.49
Kansas	7,767	1.91
New Mexico	3,488	0.86
Oklahoma	2,741	0.67
Oregon	6,413	1.58
Texas	105,135	25.86
Utah	6,313	1.55
Washington	31,645	7.78
Total	406,621	100

Panel B: By Year

Primary Market		
	# of Issues	Percent
2001	1,473	0.98
2002	2,721	1.81
2003	1,208	0.81
2004	4,953	3.30
2005	10,192	6.79
2006	9,389	6.26
2007	9,158	6.10
2008	7,008	4.67
2009	5,683	3.79
2010	5,878	3.92
2011	5,591	3.73
2012	7,386	4.92
2013	7,648	5.10
2014	7,923	5.28
2015	12,101	8.07
2016	11,962	7.97
2017	10,361	6.91
2018	7,747	5.16
2019	8,878	5.92
2020	6,764	4.51
2021	5,989	3.99
Total	150,013	100

Secondary Market		
	# of Trades	Percent
2005	8,556	2.1
2006	12,353	3.04
2007	13,533	3.33
2008	14,586	3.59
2009	15,622	3.84
2010	15,994	3.93
2011	16,650	4.09
2012	15,821	3.89
2013	20,893	5.14
2014	18,414	4.53
2015	22,378	5.5
2016	28,903	7.11
2017	39,230	9.65
2018	52,607	12.94
2019	53,944	13.27
2020	57,137	14.05
Total	406,621	100

Table A2: Sample composition

Primary Market

	Mean	Std. Dev.	Observations
Fire Risk Change	14.91	16.84	208,223
Yield-To-Maturity	2.77	1.29	208,223
Spread (basis points)	32.02	41.98	208,223
Time to Maturity (years)	10.09	6.49	208,223
Face Issued Total (Millions USD)	2.02	6.76	208,223
$\mathbb{I}\{\text{Insured}\}$	0.28	0.45	208,223
$\mathbb{I}\{\text{Callable}\}$	0.49	0.50	208,223
$\mathbb{I}\{\text{Sinkable}\}$	0.08	0.27	208,223
$\mathbb{I}\{\text{Competitive}\}$	0.44	0.50	208,223

Secondary Market

	Mean	Std. Dev.	Observations
Fire Risk Change	12.20	15.47	531,640
Yield-To-Maturity	2.35	1.21	531,640
Spread (basis points)	52.06	60.96	531,640
Time to Maturity (years)	7.54	6.12	531,640
Bond Age (years)	3.01	2.68	531,640
Monthly Trading Volume (Thousands USD)	620.85	2,677.29	531,640
Monthly Turnover	0.23	0.55	531,640
Monthly Standard Deviation of Price	0.60	0.65	531,640
$\mathbb{I}\{\text{Insured}\}$	0.32	0.47	531,640
$\mathbb{I}\{\text{Callable}\}$	0.41	0.49	531,640
$\mathbb{I}\{\text{Sinkable}\}$	0.08	0.27	531,640

Table A3: 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 two counties to improve the representativeness of our sample. The final sample in the secondary market analysis comprises 531,640 bond-month trades spanning from 2005 to 2020, with 68,780 bonds issued by 2,458 school districts. The primary market sample consists of 208,223 bonds issued by 2,961 school districts, spanning from 2001 to 2021. Fire Risk Change is the difference between the maturity-calendar-date-group-matched interpolated weighted KBDI and the historical weighted KBDI within a district. Yield-to-Maturity is an annual interest rate that equates the present value of cash flow payments received from a bond with the monthly mean of its daily fundamental prices 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. $\mathbb{I}\{\text{Insured}\}$, $\mathbb{I}\{\text{Callable}\}$, and $\mathbb{I}\{\text{Sinkable}\}$ denote the insurance, callability, and sinkability status, respectively. $\mathbb{I}\{\text{Competitive}\}$ denotes the sales method by which the bond is traded, either through negotiation or competitive bidding.

	1	2	3	4
Δ Fire × 𝕀(Year = 2001)	7.277*	-2.534	5.736*	3.933
	(3.773)	(5.569)	(3.083)	(5.736)
Δ Fire × 𝕀(Year = 2002)	1.246	-3.329	0.528	-2.765
	(4.539)	(7.038)	(3.517)	(4.962)
Δ Fire × 𝕀(Year = 2003)	-2.402	-14.83	-1.693	-9.986
	(4.066)	(9.245)	(5.048)	(7.595)
Δ Fire × 𝕀(Year = 2004)	1.449	10.74	-0.269	3.489
	(3.458)	(10.49)	(2.741)	(5.983)
Δ Fire × 𝕀(Year = 2005)	4.286	-4.807	3.809	3.879
	(3.201)	(4.941)	(2.469)	(3.904)
Δ Fire × 𝕀(Year = 2006)	4.625*	-1.945	4.066*	0.827
	(2.788)	(4.418)	(2.387)	(3.652)
Δ Fire × 𝕀(Year = 2007)	6.359*	-1.917	4.992**	2.625
	(3.365)	(4.563)	(2.496)	(3.720)
Δ Fire × 𝕀(Year = 2008)	5.305	-4.746	2.041	-6.384
	(3.482)	(5.130)	(2.829)	(4.412)
Δ Fire × 𝕀(Year = 2009)	-14.05***	-24.05***	-15.21***	-17.38***
	(4.012)	(5.547)	(3.198)	(4.746)
Δ Fire × 𝕀(Year = 2010)	-0.924	-11.96**	-1.964	-5.073
	(3.480)	(4.675)	(2.530)	(4.685)
Δ Fire × 𝕀(Year = 2011)	-4.003	-15.15**	-5.795*	-8.266
	(3.740)	(6.050)	(3.021)	(6.931)
Δ Fire × 𝕀(Year = 2013)	2.599	-5.677	2.135	-1.140
	(2.784)	(4.672)	(2.711)	(3.774)
Δ Fire × 𝕀(Year = 2014)	3.630	-4.205	2.298	-1.567
	(2.563)	(4.412)	(2.527)	(3.989)
Δ Fire × 𝕀(Year = 2015)	12.28***	6.503	12.81***	11.46***
	(2.598)	(4.472)	(2.360)	(3.546)
Δ Fire × 𝕀(Year = 2016)	13.37***	7.182	12.13***	12.01***
	(3.131)	(5.560)	(2.465)	(3.812)
Δ Fire × 𝕀(Year = 2017)	11.01***	7.108*	10.81***	12.62***
	(3.076)	(3.952)	(2.325)	(4.340)
Δ Fire × 𝕀(Year = 2018)	18.43***	12.99***	17.27***	16.78***
	(2.866)	(4.488)	(2.527)	(4.368)
Δ Fire × 𝕀(Year = 2019)	24.50***	25.39***	25.81***	30.81***
	(3.284)	(5.345)	(2.768)	(4.794)
Δ Fire × 𝕀(Year = 2020)	26.16***	26.47***	26.12***	35.91***
	(2.938)	(6.569)	(2.870)	(6.706)
Δ Fire × 𝕀(Year = 2021)	29.44***	28.45***	27.63***	31.00***
	(3.781)	(5.700)	(2.956)	(4.707)
R^2	0.910	0.913	0.906	0.911
Δ Fire × 𝕀(Year >= 2015)	13.63***	18.67***	14.47***	20.30***
	(1.336)	(1.814)	(1.001)	(2.055)
R^2	0.909	0.913	0.905	0.910
Equal Weights	N	Y	N	Y
More Than One District Per County	Y	Y	Y	Y
Cluster for Standard Error	County	County	District	District
Number of Districts	1,881	1,881	2,961	2,961
Observations	148,461	148,461	205,694	205,694

Table A4: Wildfire risk changes and municipal credit spreads in the primary market - Robustness specification

This table reports the year-by-year and post-2014 impact of wildfire risk increases on municipal credit spreads in the primary market. 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 5 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-35), and fire potentials are interpolated using a stepwise function from the historic level (1995-2004) to the mid-century prediction (2045-2054). We define ΔFire as the difference between the maturity-calendar-date-group-matched interpolated value and the historic level, which is standardized to a mean of zero and standard deviation of one. The regression includes the bond's district-by-maturity-calendar-date-group fixed effects and district-by-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), as well as its callability and sinkability status. Column (1) presents the benchmark specification. Column (2) weights each observation by the inverse of the count of distinct bonds within each state for a specific issue year. Column (3) additionally includes bonds issued in counties that contain only one district or span across two counties. Column (4) removes geographic restrictions and applies equal weighting across states.

	1	2	3	4
Δ Fire $\times$ $\mathbb{I}$(Year = 2005)	8.588	-13.73	7.385	-8.747
	(8.404)	(13.13)	(8.783)	(9.847)
Δ Fire $\times$ $\mathbb{I}$(Year = 2006)	1.982	-17.35	3.555	-6.797
	(7.575)	(13.93)	(8.207)	(10.88)
Δ Fire $\times$ $\mathbb{I}$(Year = 2007)	3.594	-5.065	3.882	-0.608
	(5.138)	(8.305)	(6.481)	(6.533)
Δ Fire $\times$ $\mathbb{I}$(Year = 2008)	-0.224	-17.37	-1.101	-14.89*
	(6.426)	(11.55)	(5.993)	(7.694)
Δ Fire $\times$ $\mathbb{I}$(Year = 2009)	-6.011	-29.99*	-7.811	-28.66***
	(13.53)	(15.88)	(7.396)	(8.859)
Δ Fire $\times$ $\mathbb{I}$(Year = 2010)	-3.541	-20.13	-3.607	-13.13*
	(8.322)	(13.14)	(4.568)	(7.464)
Δ Fire $\times$ $\mathbb{I}$(Year = 2011)	-5.663	-14.21	-6.733	-15.51**
	(7.859)	(9.348)	(5.107)	(6.901)
Δ Fire $\times$ $\mathbb{I}$(Year = 2013)	-7.714***	-7.989	-4.999	-3.143
	(2.271)	(7.135)	(3.151)	(4.363)
Δ Fire $\times$ $\mathbb{I}$(Year = 2014)	3.197	-7.959	5.401	2.622
	(3.230)	(8.142)	(3.550)	(5.530)
Δ Fire $\times$ $\mathbb{I}$(Year = 2015)	18.45***	12.20*	20.06***	18.13***
	(4.235)	(7.051)	(4.026)	(5.273)
Δ Fire $\times$ $\mathbb{I}$(Year = 2016)	21.70***	18.73**	23.06***	25.37***
	(4.890)	(7.815)	(4.311)	(5.340)
Δ Fire $\times$ $\mathbb{I}$(Year = 2017)	21.90***	19.19**	23.98***	28.85***
	(4.833)	(7.983)	(4.529)	(5.734)
Δ Fire $\times$ $\mathbb{I}$(Year = 2018)	23.70***	20.51***	25.50***	32.37***
	(4.624)	(7.712)	(4.464)	(5.535)
Δ Fire $\times$ $\mathbb{I}$(Year = 2019)	33.21***	32.24***	35.22***	44.07***
	(5.173)	(8.005)	(4.746)	(5.905)
Δ Fire $\times$ $\mathbb{I}$(Year = 2020)	33.63***	38.14***	35.72***	47.85***
	(6.074)	(8.812)	(4.779)	(6.152)
R^2	0.760	0.713	0.754	0.702
Δ Fire $\times$ $\mathbb{I}$(Year >= 2015)	26.21***	28.75***	26.66***	30.49***
	(5.232)	(5.161)	(3.170)	(3.495)
R^2	0.760	0.713	0.753	0.701
Equal Weights	N	Y	N	Y
More Than One District Per County	Y	Y	Y	Y
Cluster for Standard Error	County	County	District	District
Number of Bonds	52,280	52,280	68,780	68,780
Number of Districts	1,641	1,641	2,458	2,458
Observations	361,194	361,194	469,381	469,381

Table A5: Wildfire risk changes and municipal credit spreads in the secondary market - Robustness specification

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

	1	2	3
Δ Fire	17.21***		
	(1.894)		
Δ Fire × $\mathbb{I}$(Year = 2001)	-14.50***	-30.52***	-0.780
	(2.236)	(2.882)	(2.546)
Δ Fire × $\mathbb{I}$(Year = 2002)	-14.01***	-34.94***	-1.577
	(2.086)	(2.883)	(2.948)
Δ Fire × $\mathbb{I}$(Year = 2003)	-22.98***	-35.96***	-7.294**
	(4.149)	(3.511)	(3.091)
Δ Fire × $\mathbb{I}$(Year = 2004)	-14.46***	-30.08***	-5.064**
	(1.995)	(2.893)	(2.079)
Δ Fire × $\mathbb{I}$(Year = 2005)	-9.492***	-21.22***	-2.091
	(1.886)	(2.448)	(1.998)
Δ Fire × $\mathbb{I}$(Year = 2006)	-13.11***	-20.72***	-1.719
	(1.809)	(1.839)	(1.904)
Δ Fire × $\mathbb{I}$(Year = 2007)	-11.36***	-16.72***	-0.560
	(1.889)	(2.243)	(2.145)
Δ Fire × $\mathbb{I}$(Year = 2008)	-26.02***	-27.68***	-1.346
	(2.298)	(2.806)	(2.160)
Δ Fire × $\mathbb{I}$(Year = 2009)	-28.68***	-32.06***	-13.47***
	(2.558)	(2.721)	(2.417)
Δ Fire × $\mathbb{I}$(Year = 2010)	-14.69***	-13.19***	-2.763
	(1.995)	(2.758)	(2.216)
Δ Fire × $\mathbb{I}$(Year = 2011)	-18.65***	-17.14***	-6.800***
	(2.472)	(2.898)	(2.473)
Δ Fire × $\mathbb{I}$(Year = 2013)	-2.163	3.785**	0.717
	(2.358)	(1.918)	(1.926)
Δ Fire × $\mathbb{I}$(Year = 2014)	9.238***	12.72***	-1.313
	(2.342)	(2.014)	(1.688)
Δ Fire × $\mathbb{I}$(Year = 2015)	13.45***	18.45***	7.703***
	(2.771)	(2.005)	(1.768)
Δ Fire × $\mathbb{I}$(Year = 2016)	24.07***	29.30***	8.143***
	(2.673)	(2.080)	(1.914)
Δ Fire × $\mathbb{I}$(Year = 2017)	24.88***	29.98***	6.713***
	(3.138)	(2.248)	(1.979)
Δ Fire × $\mathbb{I}$(Year = 2018)	24.49***	37.10***	11.51***
	(3.630)	(2.361)	(1.924)
Δ Fire × $\mathbb{I}$(Year = 2019)	43.93***	53.94***	17.86***
	(4.651)	(3.445)	(2.162)
Δ Fire × $\mathbb{I}$(Year = 2020)	32.78***	46.56***	15.71***
	(4.301)	(2.842)	(2.311)
Δ Fire × $\mathbb{I}$(Year = 2021)	31.85***	42.78***	17.58***
	(3.215)	(2.340)	(2.905)
R^2	0.732	0.869	0.903
Δ Fire	6.030***		
	(0.898)		
Δ Fire × $\mathbb{I}$(Year >= 2015)	37.83***	40.06***	12.04***
	(2.894)	(1.848)	(0.949)
R^2	0.727	0.864	0.903
District-by-Issue-Year-Month Fixed Effects	Y	Y	Y
District-by-Maturity-Calendar-Date-Group Fixed Effects	N	Y	Y
Controls	N	N	Y
Observations	381,031	378,047	378,047

Table A6: Wildfire risk changes and municipal credit spreads in the primary market - Contiguous United States (CONUS)

This table reports the year-by-year and post-2014 impact of wildfire risk increases on municipal credit spreads in the primary market. The sample includes the contiguous United States, with 381,884 bonds issued by 5,715 school districts. Standard errors are reported in parentheses, clustered at the county level. *, **, and *** indicate the corresponding p-value less than 0.10, 0.05, and 0.01, respectively. The credit spread of a bond is defined as the difference between its yield to maturity, 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 5 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-35), and fire potentials are interpolated using a stepwise function from the historic level (1995-2004) to the mid-century prediction (2045-2054). We define ΔFire as the difference between the maturity-calendar-date-group-matched interpolated value and the historic level, which is standardized to a mean of zero and standard deviation of one. The regression includes the bond's district-by-maturity-calendar-date-group fixed effects and district-by-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), as well as its callability and sinkability status.

	1	2	3
Δ Fire	41.28***		
	(3.492)		
Δ Fire × $\mathbb{I}$(Year = 2005)	-19.16***	-27.77***	9.729
	(3.978)	(7.325)	(6.450)
Δ Fire × $\mathbb{I}$(Year = 2006)	-28.90***	-40.17***	7.085
	(4.333)	(6.198)	(6.178)
Δ Fire × $\mathbb{I}$(Year = 2007)	-25.04***	-33.71***	8.584*
	(3.709)	(6.404)	(5.160)
Δ Fire × $\mathbb{I}$(Year = 2008)	-35.70***	-43.62***	3.246
	(10.29)	(11.60)	(4.670)
Δ Fire × $\mathbb{I}$(Year = 2009)	-23.92**	-28.78**	-2.482
	(11.70)	(13.50)	(10.50)
Δ Fire × $\mathbb{I}$(Year = 2010)	-13.96*	-19.42**	-0.765
	(8.134)	(8.936)	(6.440)
Δ Fire × $\mathbb{I}$(Year = 2011)	-13.75**	-18.17**	-3.679
	(6.269)	(7.776)	(6.405)
Δ Fire × $\mathbb{I}$(Year = 2013)	-10.53***	-7.127***	-4.038
	(3.862)	(2.217)	(2.512)
Δ Fire × $\mathbb{I}$(Year = 2014)	-8.252*	-2.269	5.456
	(4.804)	(3.579)	(3.754)
Δ Fire × $\mathbb{I}$(Year = 2015)	-4.991	5.469	19.12***
	(3.635)	(4.656)	(4.776)
Δ Fire × $\mathbb{I}$(Year = 2016)	8.938***	21.76***	22.44***
	(3.307)	(5.888)	(5.254)
Δ Fire × $\mathbb{I}$(Year = 2017)	6.497**	21.70***	21.88***
	(3.026)	(5.972)	(5.250)
Δ Fire × $\mathbb{I}$(Year = 2018)	5.779*	25.86***	23.75***
	(3.114)	(6.389)	(5.179)
Δ Fire × $\mathbb{I}$(Year = 2019)	22.37***	49.96***	32.13***
	(4.085)	(8.157)	(5.625)
Δ Fire × $\mathbb{I}$(Year = 2020)	25.35***	55.48***	32.31***
	(5.106)	(9.285)	(6.416)
R^2	0.553	0.679	0.771
Δ Fire	25.75***		
	(3.211)		
Δ Fire × $\mathbb{I}$(Year >= 2015)	29.46***	34.57***	23.43***
	(6.422)	(4.943)	(4.673)
R^2	0.551	0.676	0.771
District-by-Trade-Year-Month Fixed Effects	Y	Y	Y
District-by-Maturity-Calendar-Date-Group Fixed Effects	N	Y	Y
Controls	N	N	Y
Observations	642,440	639,543	637,969

Table A7: Wildfire risk changes and municipal credit spreads in the secondary market - Contiguous United States (CONUS)

This table reports the year-by-year and post-2014 impact of wildfire risk increases on municipal credit spreads in the secondary market. The sample includes the contiguous United States, with 116,644 bonds issued by 5,176 school districts. Standard errors are reported in parentheses, clustered at the county level. *, **, and *** indicate the corresponding p-value less than 0.10, 0.05, and 0.01, respectively. The credit spread of a bond is defined as the difference between its yield to maturity and its maturity-matched Municipal Market Analytics (MMA) yield benchmarks in basis points. Maturity calendar dates are grouped into intervals of 5 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-35), and fire potentials are interpolated using a stepwise function from the historic level (1995-2004) to the mid-century prediction (2045-2054). We define ΔFire as the difference between the maturity-calendar-date-group-matched interpolated value and the historic level, which is standardized to a mean of zero and standard deviation of one. The regression includes the bond's district-by-maturity-calendar-date-group fixed effects and district-by-trade-year-month fixed effects. Controls include bond's logarithm of the number of years before the maturity date and its insurance status interacted with the trade year indicator, the number of years since issuance, its monthly trading volume divided by its face value, its monthly standard deviation of prices, as well as its callability and sinkability status.

	1	2	3
Δ Fire	20.84***		
	(3.496)		
Δ Fire $\times$ $\mathbb{I}$(Year = 2001)	-16.14***	-47.49***	10.26**
	(4.700)	(8.034)	(4.793)
Δ Fire $\times$ $\mathbb{I}$(Year = 2002)	-14.87***	-44.58***	6.571
	(4.861)	(8.632)	(5.826)
Δ Fire $\times$ $\mathbb{I}$(Year = 2003)	-18.62***	-56.94***	-0.700
	(6.260)	(8.229)	(7.447)
Δ Fire $\times$ $\mathbb{I}$(Year = 2004)	-18.76***	-40.61***	2.896
	(3.468)	(4.719)	(4.001)
Δ Fire $\times$ $\mathbb{I}$(Year = 2005)	-12.78***	-29.44***	5.211
	(3.562)	(3.914)	(3.841)
Δ Fire $\times$ $\mathbb{I}$(Year = 2006)	-15.59***	-24.74***	8.006**
	(3.222)	(3.790)	(3.343)
Δ Fire $\times$ $\mathbb{I}$(Year = 2007)	-15.81***	-20.35***	8.503**
	(3.692)	(3.762)	(3.869)
Δ Fire $\times$ $\mathbb{I}$(Year = 2008)	-26.25***	-27.09***	6.258*
	(3.553)	(3.822)	(3.325)
Δ Fire $\times$ $\mathbb{I}$(Year = 2009)	-24.60***	-33.23***	-10.82***
	(3.717)	(3.405)	(3.665)
Δ Fire $\times$ $\mathbb{I}$(Year = 2010)	-13.02***	-13.09***	-1.441
	(3.321)	(2.909)	(2.704)
Δ Fire $\times$ $\mathbb{I}$(Year = 2011)	-19.89***	-21.79***	-7.297*
	(4.316)	(4.398)	(4.204)
Δ Fire $\times$ $\mathbb{I}$(Year = 2013)	0.525	3.553	3.769
	(3.808)	(3.380)	(3.271)
Δ Fire $\times$ $\mathbb{I}$(Year = 2014)	10.24***	12.23***	3.451
	(3.471)	(2.750)	(3.029)
Δ Fire $\times$ $\mathbb{I}$(Year = 2015)	15.77***	18.64***	11.13***
	(3.356)	(2.968)	(3.171)
Δ Fire $\times$ $\mathbb{I}$(Year = 2016)	24.96***	32.79***	14.20***
	(3.889)	(2.997)	(3.128)
Δ Fire $\times$ $\mathbb{I}$(Year = 2017)	29.09***	33.29***	10.91***
	(3.473)	(3.694)	(3.049)
Δ Fire $\times$ $\mathbb{I}$(Year = 2018)	29.64***	43.59***	17.24***
	(4.098)	(4.541)	(3.461)
Δ Fire $\times$ $\mathbb{I}$(Year = 2019)	47.64***	59.85***	19.82***
	(7.251)	(7.053)	(5.083)
Δ Fire $\times$ $\mathbb{I}$(Year = 2020)	44.11***	56.23***	21.96***
	(4.921)	(4.393)	(3.716)
Δ Fire $\times$ $\mathbb{I}$(Year = 2021)	37.00***	48.36***	23.51***
	(4.322)	(5.855)	(4.549)
R^2	0.683	0.864	0.910
Δ Fire	8.701***		
	(1.326)		
Δ Fire $\times$ $\mathbb{I}$(Year >= 2015)	42.83***	46.78***	11.74***
	(2.309)	(3.364)	(1.751)
R^2	0.678	0.858	0.909
District-by-Issue-Year-Month Fixed Effects	Y	Y	Y
District-by-Maturity-Calendar-Date-Group Fixed Effects	N	Y	Y
Controls	N	N	Y
Observations	149,530	148,461	148,461

Table A8: Wildfire risk changes and municipal credit spreads in the primary market - Summer Fire Weather Index (FWI)

This table reports the year-by-year and post-2014 impact of wildfire risk increases on municipal credit spreads in the primary market. The weighted summer Fire Weather Index (FWI) is used. Standard errors are reported in parentheses, clustered at the county level. *, **, and *** indicate the corresponding p-value less than 0.10, 0.05, and 0.01, respectively. The credit spread of a bond is defined as the difference between its yield to maturity, 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 5 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-35), and fire potentials are interpolated using a stepwise function from the historic level (1995-2004) to the mid-century prediction (2045-2054). We define ΔFire as the difference between the maturity-calendar-date-group-matched interpolated value and the historic level, which is standardized to a mean of zero and standard deviation of one. The regression includes the bond's district-by-maturity-calendar-date-group fixed effects and district-by-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), as well as its callability and sinkability status.

	1	2	3
Δ FIRE	48.78***		
	(8.066)		
Δ FIRE × $\mathbb{I}$(YEAR = 2005)	-19.89**	-41.20***	6.533
	(9.256)	(8.631)	(10.91)
Δ FIRE × $\mathbb{I}$(YEAR = 2006)	-28.27***	-57.90***	4.873
	(7.942)	(7.401)	(11.24)
Δ FIRE × $\mathbb{I}$(YEAR = 2007)	-26.75***	-49.94***	6.019
	(6.835)	(6.329)	(5.598)
Δ FIRE × $\mathbb{I}$(YEAR = 2008)	-32.75***	-57.71***	6.537
	(9.453)	(10.34)	(5.671)
Δ FIRE × $\mathbb{I}$(YEAR = 2009)	-14.54	-35.59**	-2.485
	(12.69)	(14.77)	(13.77)
Δ FIRE × $\mathbb{I}$(YEAR = 2010)	-1.517	-21.73**	0.838
	(8.702)	(9.522)	(8.229)
Δ FIRE × $\mathbb{I}$(YEAR = 2011)	-5.222	-20.62**	-4.443
	(6.931)	(8.121)	(7.814)
Δ FIRE × $\mathbb{I}$(YEAR = 2013)	-18.56***	-3.889	-4.398
	(4.677)	(4.180)	(3.551)
Δ FIRE × $\mathbb{I}$(YEAR = 2014)	-16.88***	2.875	7.089**
	(4.553)	(3.686)	(2.855)
Δ FIRE × $\mathbb{I}$(YEAR = 2015)	-7.754	10.18**	19.98***
	(7.199)	(4.799)	(3.748)
Δ FIRE × $\mathbb{I}$(YEAR = 2016)	5.647	28.85***	24.75***
	(7.543)	(5.744)	(4.299)
Δ FIRE × $\mathbb{I}$(YEAR = 2017)	1.219	28.87***	23.95***
	(7.515)	(5.819)	(3.954)
Δ FIRE × $\mathbb{I}$(YEAR = 2018)	-0.941	33.79***	25.70***
	(6.568)	(6.309)	(4.082)
Δ FIRE × $\mathbb{I}$(YEAR = 2019)	18.57**	60.90***	36.07***
	(7.809)	(7.223)	(4.264)
Δ FIRE × $\mathbb{I}$(YEAR = 2020)	26.49***	69.47***	39.03***
	(7.750)	(8.095)	(5.011)
R^2	0.505	0.656	0.760
Δ FIRE	33.77***		
	(7.263)		
Δ FIRE × $\mathbb{I}$(YEAR >= 2015)	25.54***	38.65***	25.13***
	(7.355)	(4.343)	(3.367)
R^2	0.503	0.652	0.760
District-by-Trade-Year-Month Fixed Effects	Y	Y	Y
District-by-Maturity-Calendar-Date-Group Fixed Effects	N	Y	Y
Controls	N	N	Y
Observations	362,876	361,967	361,194

Table A9: Wildfire risk changes and municipal credit spreads in the secondary market - Summer Fire Weather Index (FWI)

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

	1	2	3
Δ Fire	29.13***		
	(3.788)		
Δ Fire $\times$ $\mathbb{I}$(Year = 2001)	-24.80***	-39.85***	5.398
	(4.190)	(4.995)	(4.206)
Δ Fire $\times$ $\mathbb{I}$(Year = 2002)	-22.16***	-44.97***	-0.132
	(3.669)	(4.636)	(4.694)
Δ Fire $\times$ $\mathbb{I}$(Year = 2003)	-28.61***	-47.52***	-2.630
	(5.926)	(6.015)	(4.299)
Δ Fire $\times$ $\mathbb{I}$(Year = 2004)	-24.46***	-39.81***	1.005
	(3.895)	(5.225)	(3.732)
Δ Fire $\times$ $\mathbb{I}$(Year = 2005)	-20.00***	-30.03***	2.677
	(3.782)	(4.547)	(3.388)
Δ Fire $\times$ $\mathbb{I}$(Year = 2006)	-23.80***	-29.66***	3.758
	(3.776)	(3.718)	(3.013)
Δ Fire $\times$ $\mathbb{I}$(Year = 2007)	-22.79***	-25.98***	4.422
	(3.888)	(4.219)	(3.579)
Δ Fire $\times$ $\mathbb{I}$(Year = 2008)	-35.47***	-33.84***	4.887
	(4.389)	(5.106)	(4.029)
Δ Fire $\times$ $\mathbb{I}$(Year = 2009)	-31.58***	-39.23***	-15.94***
	(4.357)	(5.297)	(4.653)
Δ Fire $\times$ $\mathbb{I}$(Year = 2010)	-20.38***	-19.63***	-1.989
	(3.443)	(3.475)	(3.577)
Δ Fire $\times$ $\mathbb{I}$(Year = 2011)	-24.61***	-22.53***	-6.271
	(4.246)	(5.028)	(4.072)
Δ Fire $\times$ $\mathbb{I}$(Year = 2013)	-6.229	1.149	1.362
	(4.383)	(2.705)	(2.718)
Δ Fire $\times$ $\mathbb{I}$(Year = 2014)	6.463*	9.869***	2.879
	(3.791)	(3.188)	(3.172)
Δ Fire $\times$ $\mathbb{I}$(Year = 2015)	8.045*	15.52***	9.924***
	(4.134)	(2.796)	(2.794)
Δ Fire $\times$ $\mathbb{I}$(Year = 2016)	19.98***	30.29***	11.72***
	(4.258)	(3.267)	(3.369)
Δ Fire $\times$ $\mathbb{I}$(Year = 2017)	23.85***	30.70***	9.769***
	(4.516)	(3.308)	(3.252)
Δ Fire $\times$ $\mathbb{I}$(Year = 2018)	21.56***	37.83***	15.62***
	(5.735)	(3.222)	(3.178)
Δ Fire $\times$ $\mathbb{I}$(Year = 2019)	44.41***	55.15***	18.28***
	(7.114)	(4.955)	(3.262)
Δ Fire $\times$ $\mathbb{I}$(Year = 2020)	33.48***	54.05***	24.22***
	(5.620)	(4.431)	(3.561)
Δ Fire $\times$ $\mathbb{I}$(Year = 2021)	25.46***	43.26***	21.71***
	(4.670)	(3.841)	(4.700)
R^2	0.699	0.863	0.907
Δ Fire	9.454***		
	(1.046)		
Δ Fire $\times$ $\mathbb{I}$(Year >= 2015)	42.53***	45.44***	11.89***
	(4.383)	(2.935)	(1.289)
R^2	0.692	0.855	0.906
District-by-Issue-Year-Month Fixed Effects	Y	Y	Y
District-by-Maturity-Calendar-Date-Group Fixed Effects	N	Y	Y
Controls	N	N	Y
Observations	125,500	124,500	124,500

Table A10: 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 5 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-35), and fire potentials are interpolated using a stepwise function from the historic level (1995-2004) to the mid-century prediction (2045-2054). We define ΔFire as the difference between the maturity-calendar-date-group-matched interpolated value and the historic level, which is standardized to a mean of zero and standard deviation of one. The regression includes the bond's district-by-maturity-calendar-date-group fixed effects and district-by-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), as well as its callability and sinkability status.

	1	2	3
Δ Fire	39.69***		
	(4.765)		
Δ Fire × $\mathbb{I}$(Year = 2005)	-15.19***	-21.80**	8.862
	(5.026)	(9.029)	(10.32)
Δ Fire × $\mathbb{I}$(Year = 2006)	-24.42***	-37.45***	2.486
	(5.494)	(8.193)	(8.645)
Δ Fire × $\mathbb{I}$(Year = 2007)	-22.36***	-31.26***	5.732
	(4.952)	(7.670)	(6.220)
Δ Fire × $\mathbb{I}$(Year = 2008)	-32.90**	-40.65***	2.794
	(14.91)	(15.36)	(6.689)
Δ Fire × $\mathbb{I}$(Year = 2009)	-18.61	-23.75	1.599
	(14.21)	(15.02)	(10.75)
Δ Fire × $\mathbb{I}$(Year = 2010)	-10.71	-14.61	2.225
	(10.11)	(9.202)	(5.688)
Δ Fire × $\mathbb{I}$(Year = 2011)	-12.51*	-14.00*	0.552
	(6.440)	(7.964)	(5.870)
Δ Fire × $\mathbb{I}$(Year = 2013)	-4.860	-5.920**	-4.608**
	(3.744)	(2.328)	(1.928)
Δ Fire × $\mathbb{I}$(Year = 2014)	1.549	-1.567	4.363
	(5.944)	(3.330)	(2.700)
Δ Fire × $\mathbb{I}$(Year = 2015)	0.537	6.724	19.15***
	(4.232)	(5.935)	(4.893)
Δ Fire × $\mathbb{I}$(Year = 2016)	13.59***	25.18***	22.77***
	(3.833)	(8.217)	(5.500)
Δ Fire × $\mathbb{I}$(Year = 2017)	11.84***	25.40***	23.01***
	(3.925)	(8.943)	(6.026)
Δ Fire × $\mathbb{I}$(Year = 2018)	10.83***	30.28***	23.97***
	(3.821)	(9.199)	(5.629)
Δ Fire × $\mathbb{I}$(Year = 2019)	28.87***	55.86***	32.49***
	(5.309)	(11.69)	(6.545)
Δ Fire × $\mathbb{I}$(Year = 2020)	35.88***	63.82***	33.81***
	(5.602)	(12.66)	(7.256)
R^2	0.530	0.665	0.763
Δ Fire	27.32***		
	(3.967)		
Δ Fire × $\mathbb{I}$(Year >= 2015)	32.71***	37.14***	23.89***
	(8.508)	(8.444)	(6.801)
R^2	0.527	0.661	0.763
District-by-Trade-Year-Month Fixed Effects	Y	Y	Y
District-by-Maturity-Calendar-Date-Group Fixed Effects	N	Y	Y
Controls	N	N	Y
Observations	291,555	290,757	290,078

Table A11: 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 and its maturity-matched Municipal Market Analytics (MMA) yield benchmarks in basis points. Maturity calendar dates are grouped into intervals of 5 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-35), and fire potentials are interpolated using a stepwise function from the historic level (1995-2004) to the mid-century prediction (2045-2054). We define ΔFire as the difference between the maturity-calendar-date-group-matched interpolated value and the historic level, which is standardized to a mean of zero and standard deviation of one. The regression includes the bond's district-by-maturity-calendar-date-group fixed effects and district-by-trade-year-month fixed effects. Controls include bond's logarithm of the number of years before the maturity date and its insurance status interacted with the trade year indicator, the number of years since issuance, its monthly trading volume divided by its face value, its monthly standard deviation of prices, as well as its callability and sinkability status.

	1	2	3
Δ Fire $\times$ $\mathbb{I}$(Year = 2001)	7.277*	6.533	5.689
	(3.773)	(3.973)	(3.980)
Δ Fire $\times$ $\mathbb{I}$(Year = 2002)	1.246	-0.162	-1.467
	(4.539)	(4.733)	(4.646)
Δ Fire $\times$ $\mathbb{I}$(Year = 2003)	-2.402	-3.920	-4.743
	(4.066)	(4.323)	(4.112)
Δ Fire $\times$ $\mathbb{I}$(Year = 2004)	1.449	1.702	0.650
	(3.458)	(3.539)	(3.483)
Δ Fire $\times$ $\mathbb{I}$(Year = 2005)	4.286	3.773	3.252
	(3.201)	(3.447)	(3.338)
Δ Fire $\times$ $\mathbb{I}$(Year = 2006)	4.625*	3.360	2.849
	(2.788)	(2.956)	(2.845)
Δ Fire $\times$ $\mathbb{I}$(Year = 2007)	6.359*	5.295	5.021
	(3.365)	(3.527)	(3.431)
Δ Fire $\times$ $\mathbb{I}$(Year = 2008)	5.305	4.385	6.853**
	(3.482)	(3.541)	(3.469)
Δ Fire $\times$ $\mathbb{I}$(Year = 2009)	-14.05***	-10.04**	-9.594**
	(4.012)	(4.278)	(4.013)
Δ Fire $\times$ $\mathbb{I}$(Year = 2010)	-0.924	-1.881	-3.028
	(3.480)	(3.477)	(3.626)
Δ Fire $\times$ $\mathbb{I}$(Year = 2011)	-4.003	-4.077	-3.823
	(3.740)	(4.040)	(3.924)
Δ Fire $\times$ $\mathbb{I}$(Year = 2013)	2.599	1.476	2.654
	(2.784)	(2.803)	(2.754)
Δ Fire $\times$ $\mathbb{I}$(Year = 2014)	3.630	2.530	4.324
	(2.563)	(2.725)	(2.641)
Δ Fire $\times$ $\mathbb{I}$(Year = 2015)	12.28***	11.91***	13.40***
	(2.598)	(2.765)	(2.753)
Δ Fire $\times$ $\mathbb{I}$(Year = 2016)	13.37***	14.03***	17.59***
	(3.131)	(3.260)	(3.079)
Δ Fire $\times$ $\mathbb{I}$(Year = 2017)	11.01***	9.982***	12.46***
	(3.076)	(3.172)	(3.102)
Δ Fire $\times$ $\mathbb{I}$(Year = 2018)	18.43***	16.25***	17.55***
	(2.866)	(3.105)	(3.138)
Δ Fire $\times$ $\mathbb{I}$(Year = 2019)	24.50***	21.90***	20.21***
	(3.284)	(3.401)	(3.426)
Δ Fire $\times$ $\mathbb{I}$(Year = 2020)	26.16***	27.10***	23.65***
	(2.938)	(3.088)	(2.982)
Δ Fire $\times$ $\mathbb{I}$(Year = 2021)	29.44***	30.16***	28.09***
	(3.781)	(3.722)	(3.651)
R^2	0.910	0.913	0.906
Δ Fire $\times$ $\mathbb{I}$(Year >= 2015)	13.63***	13.72***	14.81***
	(1.336)	(1.439)	(1.222)
R^2	0.909	0.913	0.906
Stepsize (years)	5	4	6
District-by-Issue-Year-Month Fixed Effects	Y	Y	Y
District-by-Maturity-Calendar-Date-Group Fixed Effects	Y	Y	Y
Controls	Y	Y	Y
Observations	148,461	148,045	148,632

Table A12: Wildfire risk changes and municipal credit spreads in the primary market - Step Size for Interpolation

This table reports the year-by-year and post-2014 impact of wildfire risk increases on municipal credit spreads in the primary market. 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 5 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-35), and fire potentials are interpolated using a stepwise function from the historic level (1995-2004) to the mid-century prediction (2045-2054). We define ΔFire as the difference between the maturity-calendar-date-group-matched interpolated value and the historic level, which is standardized to a mean of zero and standard deviation of one. The regression includes the bond's district-by-maturity-calendar-date-group fixed effects and district-by-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), as well as its callability and sinkability status. Column (1) presents the benchmark specification. Columns (2) and (3) use step sizes of 4 and 6 years, respectively, for interpolating wildfire risks.

	1	2	3
Δ Fire × $\mathbb{I}$(Year = 2005)	8.588	4.462	-6.28
	(8.404)	(9.972)	(8.366)
Δ Fire × $\mathbb{I}$(Year = 2006)	1.982	-0.593	-4.905
	(7.575)	(8.485)	(6.973)
Δ Fire × $\mathbb{I}$(Year = 2007)	3.594	3.857	-0.101
	(5.138)	(5.510)	(5.043)
Δ Fire × $\mathbb{I}$(Year = 2008)	-0.224	-3.458	-4.004
	(6.426)	(8.786)	(7.275)
Δ Fire × $\mathbb{I}$(Year = 2009)	-6.011	-0.493	-9.601
	(13.53)	(12.67)	(13.96)
Δ Fire × $\mathbb{I}$(Year = 2010)	-3.541	-1.173	-10.84
	(8.322)	(9.943)	(11.40)
Δ Fire × $\mathbb{I}$(Year = 2011)	-5.663	-3.743	-10.43
	(7.859)	(8.213)	(8.179)
Δ Fire × $\mathbb{I}$(Year = 2013)	-7.714***	-5.601***	-6.618**
	(2.271)	(2.097)	(2.590)
Δ Fire × $\mathbb{I}$(Year = 2014)	3.197	1.699	-0.244
	(3.230)	(2.405)	(2.950)
Δ Fire × $\mathbb{I}$(Year = 2015)	18.45***	17.71***	16.46***
	(4.235)	(3.059)	(3.739)
Δ Fire × $\mathbb{I}$(Year = 2016)	21.70***	20.97***	20.53***
	(4.890)	(3.863)	(5.141)
Δ Fire × $\mathbb{I}$(Year = 2017)	21.90***	19.05***	18.62***
	(4.833)	(3.728)	(5.320)
Δ Fire × $\mathbb{I}$(Year = 2018)	23.70***	19.77***	19.46***
	(4.624)	(3.541)	(5.084)
Δ Fire × $\mathbb{I}$(Year = 2019)	33.21***	27.88***	26.05***
	(5.173)	(3.848)	(5.275)
Δ Fire × $\mathbb{I}$(Year = 2020)	33.63***	30.71***	27.23***
	(6.074)	(4.470)	(6.012)
R^2	0.760	0.764	0.758
Δ Fire × $\mathbb{I}$(Year >= 2015)	26.21***	23.09***	25.42***
	(5.232)	(4.370)	(5.859)
R^2	0.760	0.764	0.757
Stepsize (years)	5	4	6
District-by-Trade-Year-Month Fixed Effects	Y	Y	Y
District-by-Maturity-Calendar-Date-Group Fixed Effects	Y	Y	Y
Controls	Y	Y	Y
Observations	361,194	360,928	361,384

Table A13: Wildfire risk changes and municipal credit spreads in the secondary market - Step Size for Interpolation

This table reports the year-by-year and post-2014 impact of wildfire risk increases on municipal credit spreads in the secondary market. Standard errors are reported in parentheses. *, **, and *** indicate the corresponding p-value less than 0.10, 0.05, and 0.01, respectively. The credit spread of a bond is defined as the difference between its yield to maturity and its maturity-matched Municipal Market Analytics (MMA) yield benchmarks in basis points. Maturity calendar dates are grouped into intervals of 5 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-35), and fire potentials are interpolated using a stepwise function from the historic level (1995-2004) to the mid-century prediction (2045-2054). We define ΔFire as the difference between the maturity-calendar-date-group-matched interpolated value and the historic level, which is standardized to a mean of zero and standard deviation of one. The regression includes the bond's district-by-maturity-calendar-date-group fixed effects and district-by-trade-year-month fixed effects. Controls include bond's logarithm of the number of years before the maturity date and its insurance status interacted with the trade year indicator, the number of years since issuance, its monthly trading volume divided by its face value, its monthly standard deviation of prices, as well as its callability and sinkability status. Column (1) presents the benchmark specification. Columns (2) and (3) use step sizes of 4 and 6 years, respectively, for interpolating wildfire risks.

	1	2	3	4	5
Δ Fire × $\mathbb{I}$(Year >= 2015)	11.23***	11.54***	11.87***	6.765***	4.795**
	(1.791)	(1.803)	(1.911)	(2.144)	(2.154)
Δ Heat × $\mathbb{I}$(Year >= 2015)	14.20***	14.12***	13.72***	17.55***	19.77***
	(1.741)	(1.778)	(1.556)	(1.714)	(1.402)
R^2	0.910	0.910	0.910	0.911	0.911
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
District-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
Observations	148,461	148,461	148,461	148,461	148,461

Table A14: 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 5 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-35), and fire potentials are interpolated using a stepwise function from the historic level (1995-2004) to the mid-century prediction (2045-2054). We define ΔFire as the difference between the maturity-calendar-date-group-matched interpolated value and the historic level, which is standardized to a mean of zero and standard deviation of one. Similarly, we define ΔHeat as the difference between the maturity-calendar-date-group-matched interpolated value and the historic level, which is standardized to a mean of zero and standard deviation of one. The regression includes the bond's district-by-maturity-calendar-date-group fixed effects and district-by-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), as well as its callability and sinkability status.

	1	2	3	4	5
Δ Fire $\times$ $\mathbb{I}$(Year >= 2015)	20.20***	21.13***	22.77***	13.30**	4.999
	(4.775)	(4.703)	(4.660)	(5.965)	(4.259)
Δ Heat $\times$ $\mathbb{I}$(Year >= 2015)	30.67***	31.52***	28.85***	32.53***	36.84***
	(4.646)	(4.454)	(3.828)	(4.326)	(3.840)
R^2	0.761	0.761	0.761	0.761	0.762
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
District-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
Observations	361,194	361,194	361,194	361,194	361,194

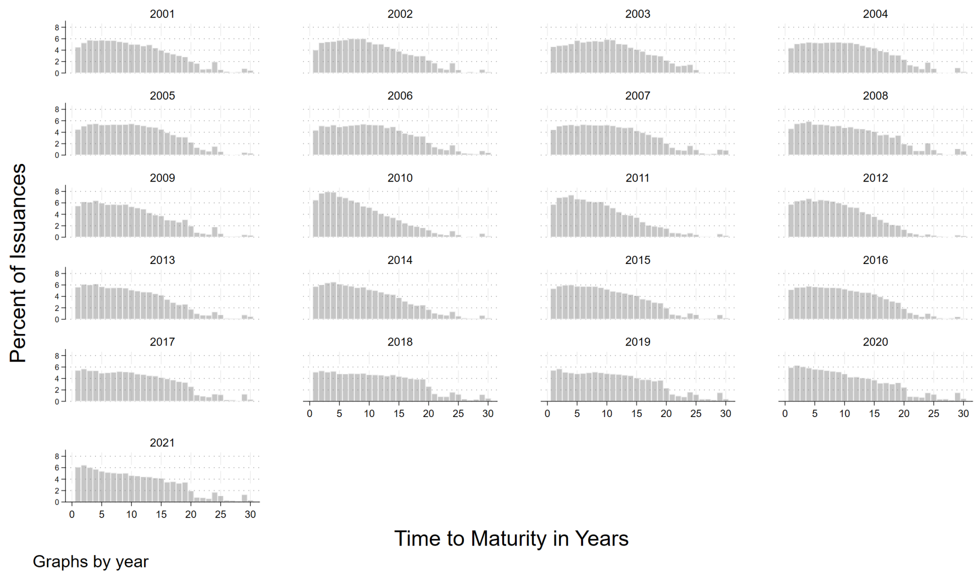
Table A15: Wildfire risk changes and municipal credit spreads in the secondary market - Heat risks

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 and its maturity-matched Municipal Market Analytics (MMA) yield benchmarks in basis points. Maturity calendar dates are grouped into intervals of 5 years (e.g., Santa Barbara Unified School District bonds maturing in 2030-35), and fire potentials are interpolated using a stepwise function from the historic level (1995-2004) to the mid-century prediction (2045-2054). We define ΔFire as the difference between the maturity-calendar-date-group-matched interpolated value and the historic level, which is standardized to a mean of zero and standard deviation of one. Similarly, we define ΔHeat as the difference between the maturity-calendar-date-group-matched interpolated value and the historic level, which is standardized to a mean of zero and standard deviation of one. The regression includes the bond's district-by-maturity-calendar-date-group fixed effects and district-by-trade-year-month fixed effects. Controls include bond's logarithm of the number of years before the maturity date and its insurance status interacted with the trade year indicator, the number of years since issuance, its monthly trading volume divided by its face value, its monthly standard deviation of prices, as well as its callability and sinkability status.

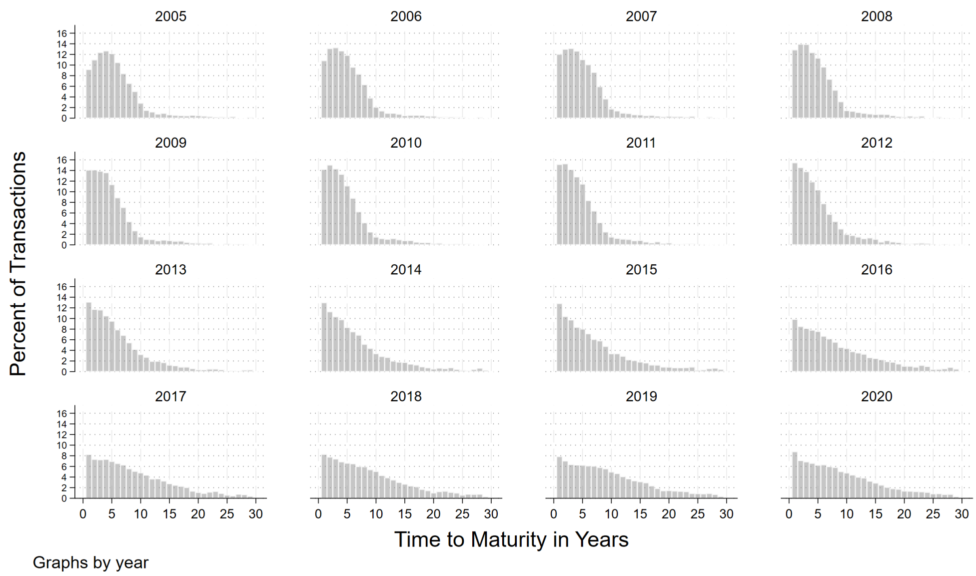
	Mean	Std. Dev.	Observations
Fire Risk Change	28.84	28.85	18,040
Median value of owner-occupied housing units in 2017 USD (in thousands of dollars)	260.26	224.63	18,040
Mean household income in 2017 USD (in thousands of dollars)	74.94	28.72	18,040
Unemployment rate (%)	4.92	2.42	18,040

Table A16: Summary statistics for socioeconomic data

This table reports the summary statistics for the variables used in the sample. The sample comprises 18,040 district-year observations spanning from 2009 to 2021, with 1,885 school districts.



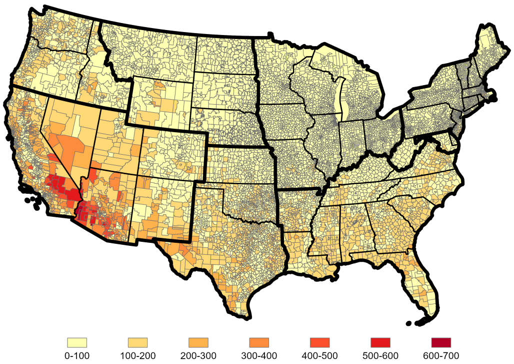
(a) Primary school district bond market



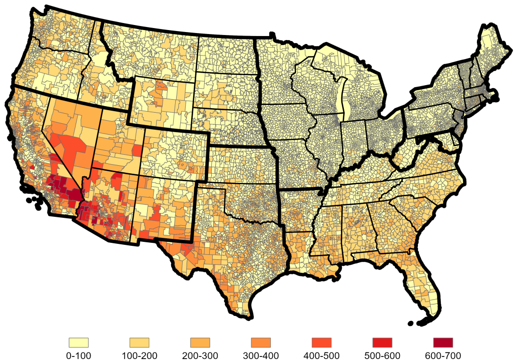
(b) Secondary school district bond market

Figure A1: Distribution of time to maturity by year

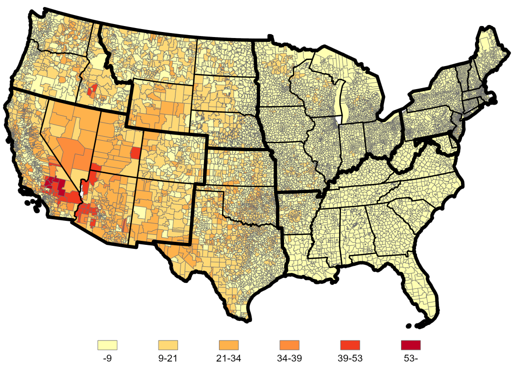
This figure displays the distribution of time-to-maturity (in years) for the school district bonds traded each year in our benchmark regression. Our primary and secondary school district bond market data cover trades from 2001 to 2021 and issues from 2005 to 2020.



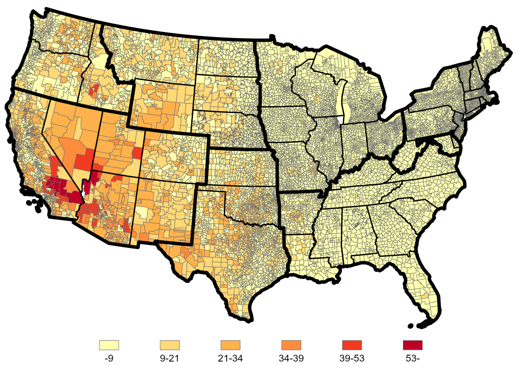
(a) Historic housing unit-weighted KBDI (1995-2004)



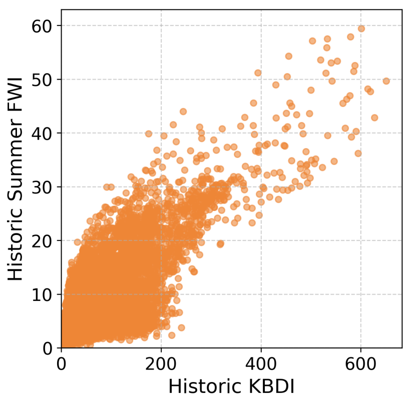
(b) Mid-century housing unit-weighted KBDI (2045-2054)



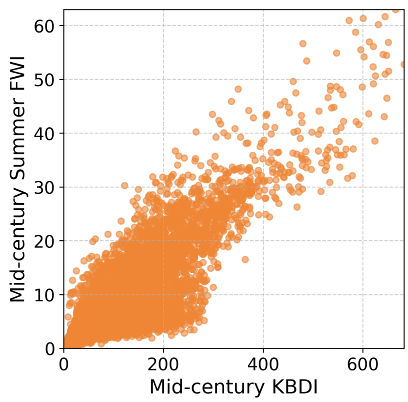
(c) Historic housing unit-weighted summer FWI (1995-2004)



(d) Mid-century housing unit-weighted summer FWI (2045-2054)



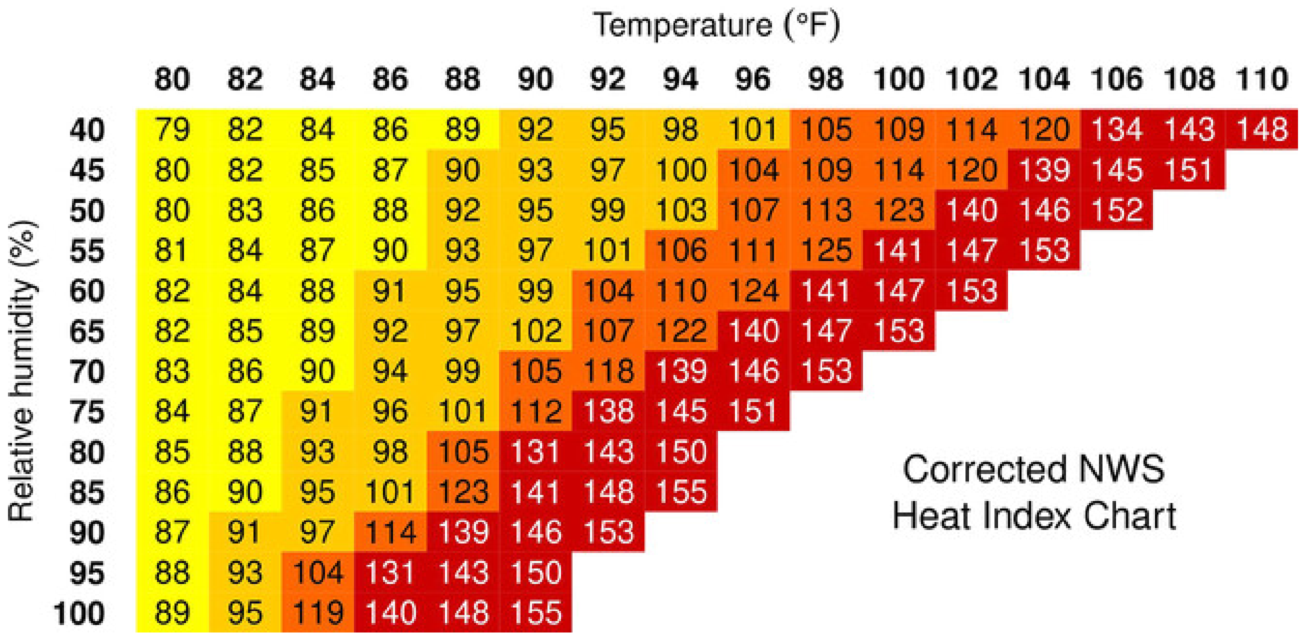
(e) Scatter plot: KBDI vs. FWI (1995-2004)



(f) Scatter plot: KBDI vs. FWI (2045-2054)

Figure A2: Alternative measures of wildfire risks

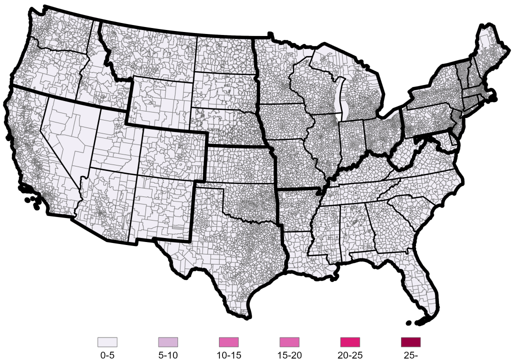
This figure maps school districts' housing unit-weighted Keetch-Byram Drought Index (KBDI) and housing unit-weighted summer Fire Weather Index (FWI), calculated from Brown et al. (2021) and ANL (2023), respectively, along with their two-way scatter plots. KBDI values exceeding 400 and FWI values exceeding 21 indicate late summer or early fall weather conditions associated with an elevated risk of wildfire occurrences (Liu et al., 2010; ANL, 2023).



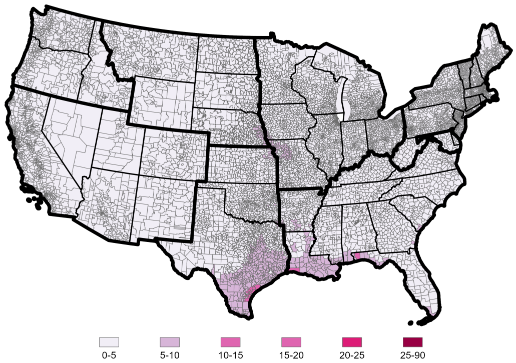
	80	82	84	86	88	90	92	94	96	98	100	102	104	106	108	110
40	79	82	84	86	89	92	95	98	101	105	109	114	120	134	143	148
45	80	82	85	87	90	93	97	100	104	109	114	120	139	145	151	
50	80	83	86	88	92	95	99	103	107	113	123	140	146	152		
55	81	84	87	90	93	97	101	106	111	125	141	147	153			
60	82	84	88	91	95	99	104	110	124	141	147	153				
65	82	85	89	92	97	102	107	122	140	147	153					
70	83	86	90	94	99	105	118	139	146	153						
75	84	87	91	96	101	112	138	145	151							
80	85	88	93	98	105	131	143	150								
85	86	90	95	101	123	141	148	155								
90	87	91	97	114	139	146	153									
95	88	93	104	131	143	150										
100	89	95	119	140	148	155										

Figure A3: Corrected Heat Index chart on the website of the National Weather Service (NWS)

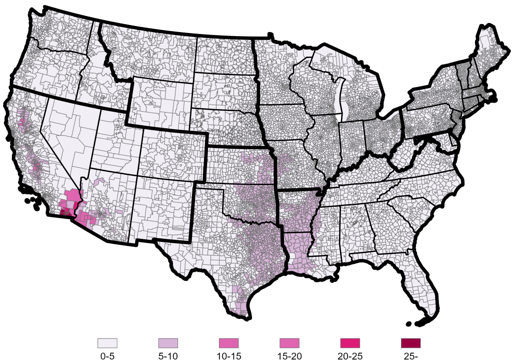
Adapted from "Extending the heat index," by Y. Lu and D. M. Romps, 2022, Journal of Applied Meteorology and Climatology, 61 (10), 1367-1383 (10.1175/JAMC-D-22-0021.1). Copyright 2022 American Meteorological Society.



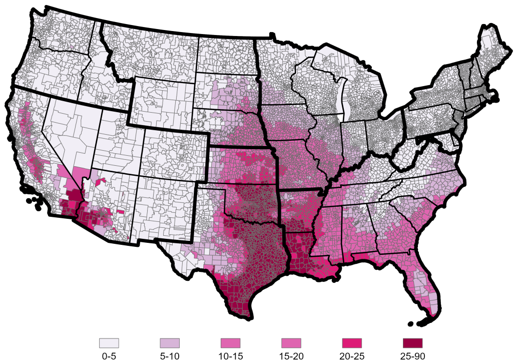
(a) Historic number of summer days with a seasonal average daily maximum heat index above 125 (1995-2004)



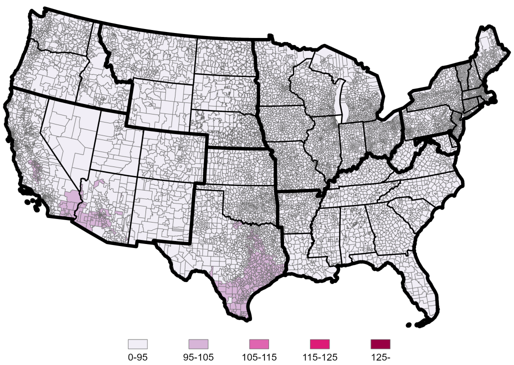
(b) Mid-century number of summer days with a seasonal average daily maximum heat index above 125 (2045-2054)



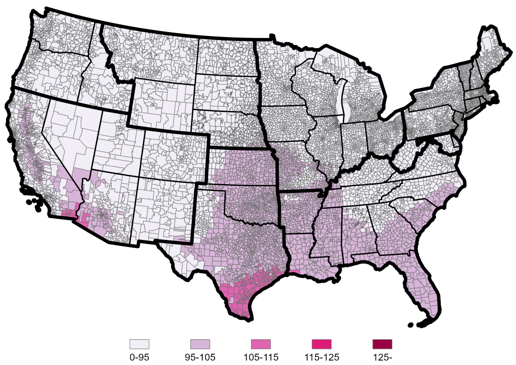
(c) Historic number of summer days with a seasonal average daily maximum heat index above 105 (1995-2004)



(d) Mid-century number of summer days with a seasonal average daily maximum heat index above 105 (2045-2054)



(e) Historic seasonal average daily maximum heat index (1995-2004)



(f) Mid-century seasonal average daily maximum heat index (2045-2054)

Figure A4: Population-weighted economic heat Risks

This figure maps school districts' population-weighted number of summer days with a seasonal average daily maximum heat index above 125 and 105 degree, as well as the seasonal average daily maximum heat index, calculated from ANL (2023). Heat index values exceeding 105 indicate that sunstroke, heat cramps, or heat exhaustion are likely, and heat stroke is possible with prolonged exposure and/or physical activity.

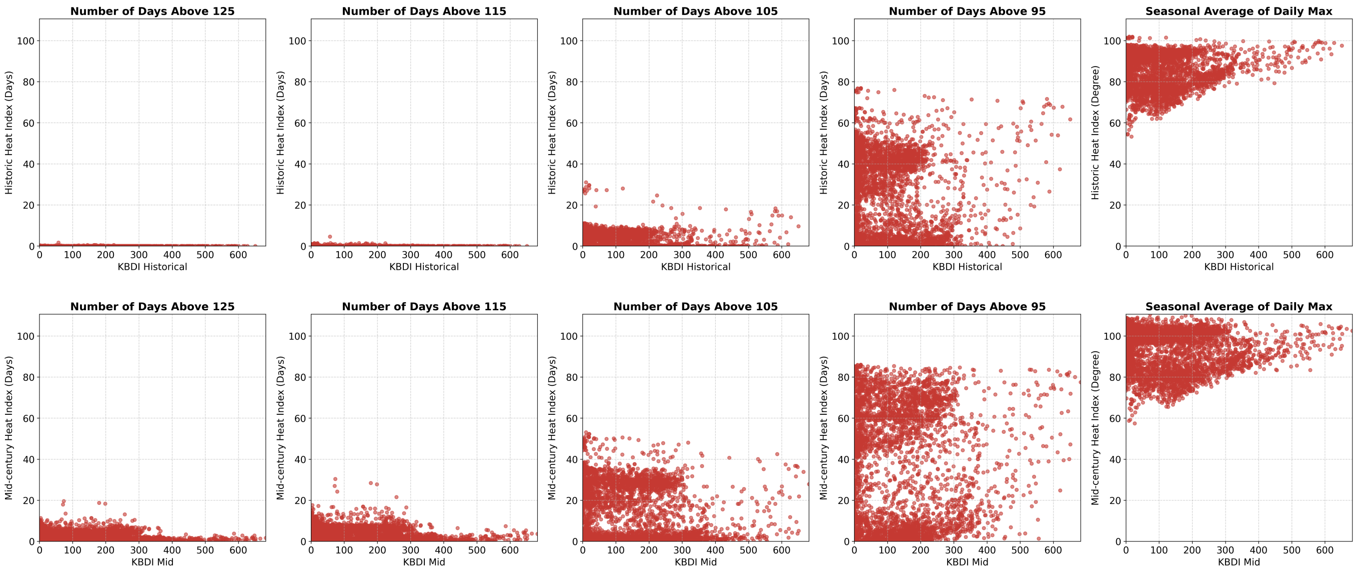


Figure A5: Scatter plot: KBDI versus Heat Index

This figure displays a two-way scatter plot of housing unit-weighted KBDI 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).

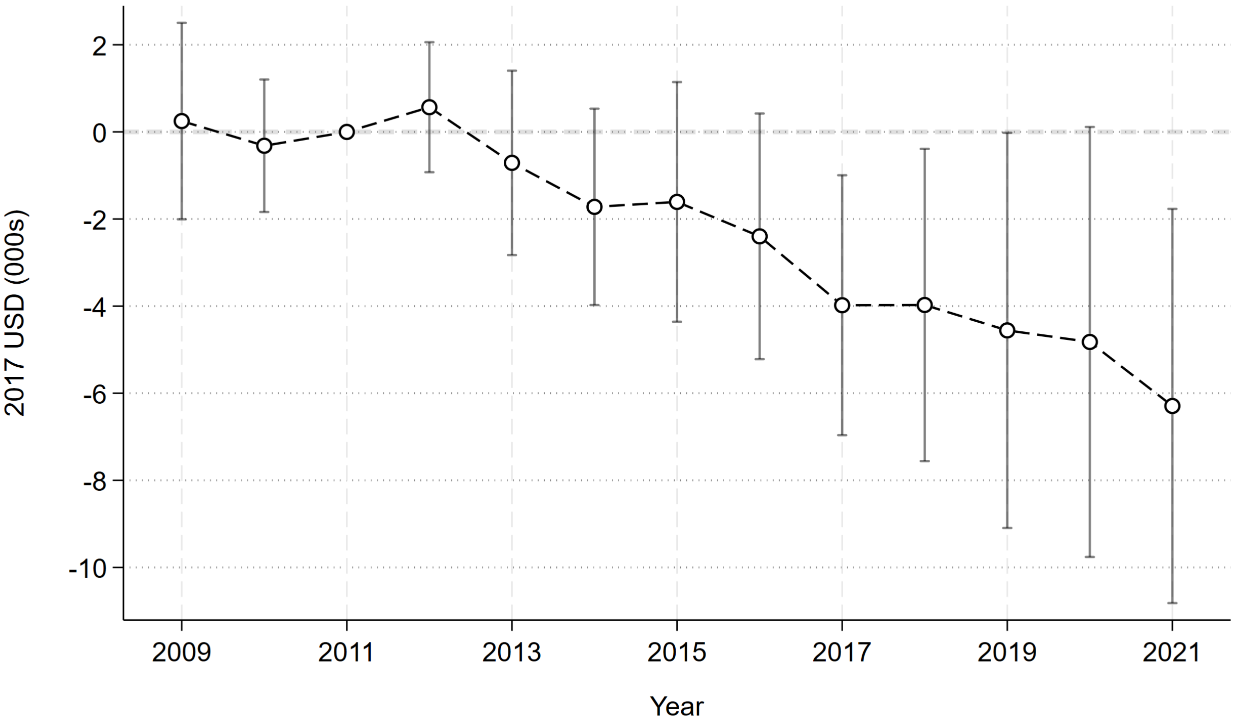


Figure A6: Association between future wildfire risk changes and housing values

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 9, with the baseline period set to 2011. The vertical lines represent the 95% confidence intervals, with standard errors clustered at the county level. We exclude all observations starting from the year in which they were first impacted by large-scale wildfires. We define ΔFire as the difference between mid-century and historic weighted KBDI values per district. The regression includes district fixed effects and county-by-year fixed effects. Additionally, we control for the mean household income and unemployment rate of each district.

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