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ABSTRACT

We exploit regional variations in exposure to heat stress to study if physical climate risk is priced in municipal bond, corporate bond and equity markets. We find consistent evidence across asset classes that local exposure to heat stress is associated with higher yield spreads for bonds and higher conditional expected returns for stocks. These results are observed robustly starting in 2013–15. The fact that heat stress premium is (a) positive, (b) economically substantial, and (c) present across comprehensive samples of multiple asset classes is consistent with macroeconomic models where climate change has a direct negative impact on aggregate consumption.

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Introduction

Climate change is expected to cause direct damages to society by amplifying many natural hazards so that understanding how climate-related risks affect municipal and corporate cost of capital is crucial for knowing whether undertaking measures to limit these damages is incentive-compatible in the economy. While concerns about global warming initiated much of the research in climate science and its attendant financial risks, implications of heat stress exposure for asset prices are surprisingly not been extensively studied. Indeed, among the candidate climate change risks, heat stress exposure stands out quantitatively as the most significant contributor to economic damages. Estimates by Hsiang et al. (2017) suggest that by the end of the century, annual damages in the United States associated with direct consequences of extreme heat – such as an increase in energy expenditures and mortality, and a decrease in labor productivity – will amount to several percentages of GDP.[1] Relatedly, Jones et al. (2020) has shown that heat stress increases the risk of wildfires, which can cause massive damages to property and human lives. This, in turn, can increase bankruptcy risk of municipalities and utilities, raising their cost of capital.[2] However, economic exposure to heat stress extends much beyond wildfire risk, even when the risk manifests only in a gradual

[1]Recent climate finance literature has also shown that the extreme temperatures are already affecting various economic outcomes such as firm earnings (Addoum et al., 2023, Pankratz et al., 2023), attention to global warming (Choi et al., 2020), and economic growth (Colacito et al., 2019). As a recent example of direct impact of heat stress on outdoor labor productivity, Oregon's Occupational Safety and Health Administration (OSHA) adopted a new rule in June 2022 to protect outdoor workers from excessive heat by requiring employers to provide an increasing number of heat rest breaks when ambient temperatures reach 90 and 100 degrees Fahrenheit, respectively (*Rules to Address Employee and Labor Housing Occupant Exposure to High Ambient Temperatures*, Oregon OSHA Administrative Order 3-2022). In July 2024, Biden White House proposed similar rule at federal level.

[2]As an important recent example of heat risk borne by investors, California experienced massive wildfires in 2017 and 2018, which imposed a heavy cost on the communities living in the affected areas, and on the fiscal health of the affected counties (e.g. *Paradise, the Wildfire-Ravaged California Town, Warns of Municipal Bond Default*, WSJ, July 22, 2022). California's largest utility, Pacific Gas and Electric (PG&E) filed for Chapter 11 bankruptcy in January 2019 on a total of about $30 billion of liabilities after these wildfires across the state. The stock price of PG&E fell precipitously following the financial distress. The Wall Street Journal called it the "first climate change bankruptcy" (*PG&E: The First Climate-Change Bankruptcy, Probably Not the Last*, WSJ, January 18, 2019). The bankruptcy imposed costs, by way of reduced utility services and increased costs, on families residing in affected areas as well as on municipal bondholders who invested in the debt issued by PG&E. In addition, tax payers also were affected as assistance was provided by Federal Emergency Management Agency (FEMA) and other federal agencies.

manner that is less starkly visible. Indeed, distinctly among the types of physical risk, many effects of heat stress are not associated with immediately measurable, damage-causing events, rendering the risk effectively uninsurable. In recent recognition of the relative intangibility of heat dangers, consideration is being given to naming heat waves and exploring ranking systems as is presently done for storms.[3]

In summary, while exposure to heat stress is a key channel through which climate change is projected to cause damage to the economy, we know relatively little about how exposure to this risk affects asset prices and the cost of borrowing by entities that are exposed to it. We fill this important gap in the literature.

We employ two measures of heat stress exposure: (i) Hsiang et al. (2017)'s Spatial Empirical Adaptive Global-to-Local Assessment System (SEAGLAS) estimates of economic damages from climate change in the United States at county-level using data up to 2013, which we also aggregate up to corporate level using Dun & Bradstreet's Global Archive Files on the location of and employment at company establishments, and (ii) Moody's 427 measures of climate stress exposure as of December 2019 for each firm in the S&P 500 based on the locations of its physical assets such as production plants and offices, with a similar measure as of Feb 2020 for municipalities. We study the impact of these heat stress exposure measures on prices in three financial asset classes over the period 2006-2020: (a) credit spreads on municipal bonds, (b) credit spreads on corporate bonds, and (c) conditional levered and unlevered expected return on stocks. We find consistent evidence across asset classes that local exposure to heat stress is associated with higher yield spreads for bonds, especially for lower-quality and longer-maturity bonds, as well as with higher conditional expected returns for stocks, these effects being observed robustly starting in 2013–15. To the best of our knowledge, our paper is the first in the literature to explore and provide evidence of a consistent link between heat stress and its systematic impact on prices in these three asset

[3]See Center for Law, Energy, and the Environment (2020) for an extensive study of the practical difficulties of developing an insurance market for heat stress, and *California debates naming heatwaves to underscore deadly risk of extreme heat*, The Guardian, 1 March 2022.

classes in the form of increased credit spreads and risk premia.

The main empirical challenge when estimating the effect of physical climate risk exposure on asset prices is that they may be correlated with some other important sources of cash flow risk. We tackle this problem directly with flexible credit rating x year fixed effects to control for time-varying effects of issuer-level heterogeneity in overall creditworthiness, essentially allowing us to vary physical climate risk exposure while keeping other major sources of cash flow risks fixed. In most cases, using credit ratings to control for other time-varying cash flow risks would constitute a "bad control problem", because any sufficiently meaningful risk exposure should have a direct impact on credit ratings. However, we argue and provide evidence that physical climate risks have had, until very recently, limited impact on credit ratings due to the high degree of model uncertainty associated with climate change damage projections.

In principle, credit ratings allow us to directly control for potentially confounding risk factors, allowing us to isolate the effect of climate risk on credit spreads. However, in practice credit ratings are an imperfect proxy for issuers' creditworthiness, both because of their discrete nature and given potential biases and omissions in the credit rating process. Hence, we also directly control for past realized extreme heat events, issuers' transition risk exposures, and various proxies of local economic conditions. To further address the potential concern that our results are affected by factors not captured by ratings (and other controls), we employ the methodology of Oster (2019) to assess the maximal impact of hypothetical omitted variables on coefficient estimates. Using her bounding argument, we show that any such variables would need to be around twice as influential in determining credit spreads as the controls that we employ in order to explain our findings (see e.g. Kacperczyk and Peydró (2022) and Florackis et al. (2023) for similar approaches in closely related contexts). In addition, we validate our primary methodology by confirming the results hold qualitatively and quantitatively for municipal bonds when we employ a "synthetic control" approach that matches bonds with high and low heat stress exposures in other bond and municipality characteristics.

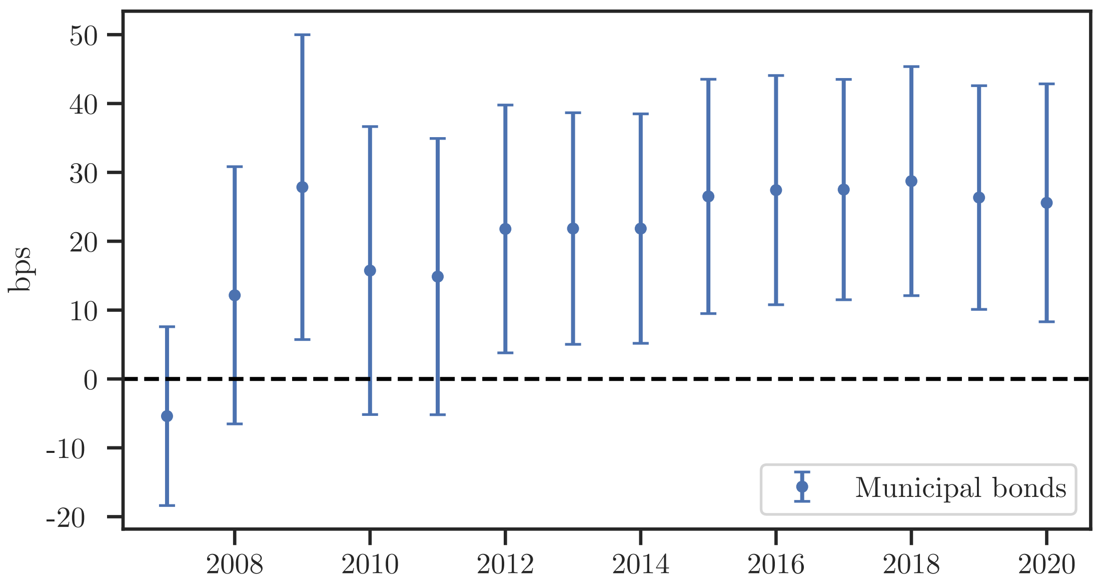
Our main findings, summarized for the SEAGLAS measure in Figure 1, are as follows. For municipal bonds, we find that exposure to increase in heat stress related annual damages that equal 1% of GDP are associated with around 25 basis points (bps) higher credit spreads compared to a municipality not exposed to any increases in such losses (see Panel A).[4] For the 427 measure, we find that a one standard deviation increase in heat stress exposure is associated with yield spreads that are higher by around 5 bps. Importantly, adding flexible credit rating fixed effects to control for issuer-level heterogeneity in overall creditworthiness has little impact on our results. Our results here suggest that municipalities in locations with higher heat stress exposure find access to bond markets more expensive. This result is important as these are precisely the ones which need capital to invest more in climate-risk abatement projects.

The positive spread we estimate only emerges in the second half of our sample starting around 2013, consistent with earlier observations (e.g., Goldsmith-Pinkham et al., 2023, Giglio et al., 2021) that attention to climate change significantly increased during this time period. The difference in spreads is mainly coming from sub-samples where the impact of long-term climate risk on creditworthiness is likely to be strongest: bonds with long maturity or low credit rating, and revenue-only bonds issued by competitive enterprises and utilities that do not have the general tax collections to support their credit repayments.

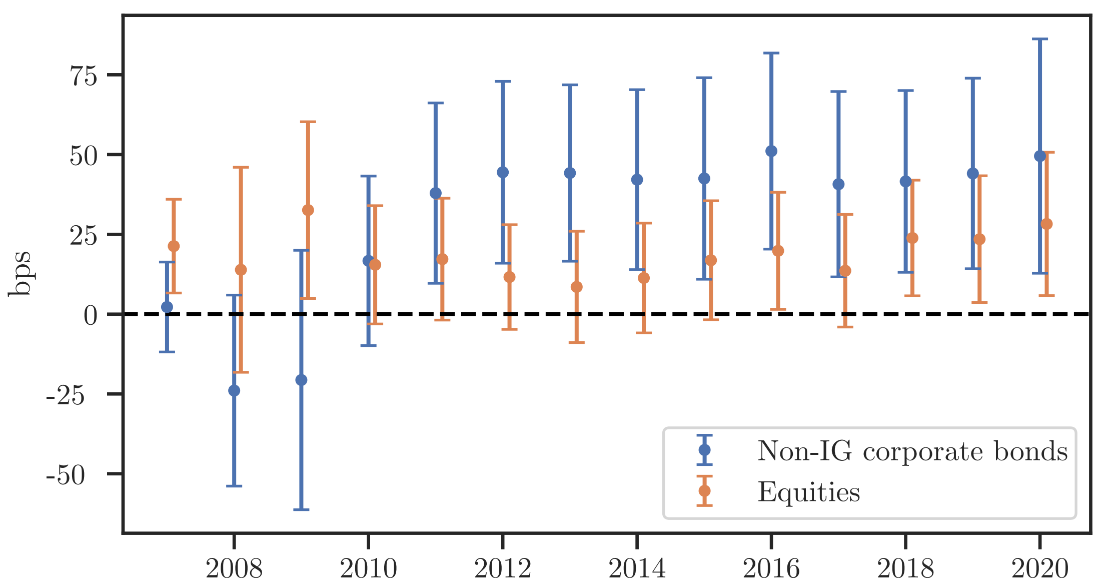
We find similar results in corporate bond spreads. For sub-investment grade corporate bonds, a company that is located in a county whose heat-related annual damages are expected to increase by 1% of GDP due to climate change have yield spread that are higher by around 45 bps compared to a company not exposed to such damages (see Figure 1 Panel B). We find little effect for investment grade bond spreads. Unlike municipal bonds whose claims are often subordinated to the pension fund claims on municipalities,[5] corporate bonds are senior

[4] Throughout the text, we summarize our year-by-year estimates by taking the average estimate between 2013 and 2020 and rounding it to the nearest multiple of 5 bps.

[5] This type of subordination was vividly illustrated in the bankruptcies of Detroit and Puerto Rico.



(a)



(b)

Figure 1: **Estimated impact of heat score on spreads and expected returns.** The figure shows year-by-year coefficient estimates and 95% confidence interval on how one standard deviation increase in heat stress exposure affects credit spreads (municipal bonds and non-investment grade corporate bonds) and conditional expected returns (equities). See Tables 3 (Column 4), Table 6 (Column 6), and Table 8 (Panel A Column 2) for full results.

to equity holders and thus are better protected, especially if the issuer is of investment grade. Moreover, unlike municipalities, counties and utilities that have fixed locations, a corporate entity can shift its employment and possibly even physical assets to mitigate climate-related risks, but such mitigation is likely expensive to undertake for firms with high leverage (as documented in case of employment by Acharya et al., 2023). Overall, this suggests that the heat stress exposure impact in corporate claims are likely borne more by high-yield bond investors (and equity holders, as we will see below) who have a lower priority in the corporate capital structure.

Next, we examine the impact of heat stress exposure on corporate credit spreads controlling for default risk measured using Moody's KMV's EDF, which uses a structural model based distance-to-default and maps it into a statistical probability of default using historical default experience data (as such, it should in principle include both climate damages and non-climate cash flow risk). We find that after controlling for the effect of firm-level EDF on spreads, the residual effect of heat stress on spreads remains positive and significant, and is about 40% of the magnitude estimated without controlling for the firm-level EDF. Together, these results can be interpreted as the risk premium on climate damages being somewhat higher than that on the non-climate cash flow risk in firm-level EDFs.

One limitation of studying credit spreads is that it does not distinguish between high spreads being driven by expected climate damages (cash flow channel) and premium on this risk (discount rate channel). Hence, to make further progress in distinguishing expected cash flows from discount rates, we next turn our attention on the pricing of U.S. stocks. The measure for conditional expected return introduced by Martin and Wagner (2019) allows us to disentangle discount rates from expected cash flows. We find that an 1% of GDP increase in heat-related damages is associated on average with around 20 bps increase in annual expected returns.

We recognize that our earlier results on the impact of heat stress on credit spreads imply that a firm's market leverage is affected by heat stress exposure too; structural models of credit risk would in turn imply that this effect on leverage would amplify any non-climate related risk premia in our measurement of expected returns on equity. To address this concern, we unlever our measure of conditional expected returns (following Doshi et al., 2019) and find that the effect of heat stress exposure on unlevered returns remains significant though its magnitude is on average somewhat lower at 15 bps increase per annum. Also consistent with our earlier findings in municipal bond markets, this impact of heat stress on expected return on equity first emerged around 2015 with little evidence during earlier years.[6]

Overall, we find economically substantial effects of heat stress on municipal and corporate cost of capital. For bonds, the yield spread effect can be both due to the cash flow channel (where increased expected losses increase spreads) and risk premium channel (which could be positive or negative). Given that we find positive effect on conditional expected returns on equities (that only reflects the discount rate channel), it is likely that the bond yields reflect both compensation for increased expected losses, and a positive risk premium associated with such losses. Importantly, the positive risk premium on heat risk exposure is consistent with macroeconomic models where climate change has a direct negative impact on aggregate consumption (e.g., Weitzman, 2012, 2014; Bansal et al., 2021) so that climate-change exposure emerges as an adversely priced risk in traded securities, and inconsistent with models wherein the climate change risk premium is predicted to be negative (e.g., Nordhaus and Boyer, 2003; Nordhaus, 2008) wherein climate change damages arise primarily in states with rapid economic expansion and associated carbon emissions. This implies, for example, that any climate change adaptation investments that municipalities or companies may undertake are discounted with lower rates, making more such investments NPV positive. Indeed, the anticipation of such adaptations imply that our estimates of the risk premium, which range from 15 bps to 45 bps per annum across asset classes, are likely a lower bound on the cost-of-capital reductions from successful adaptations.

[6]Note that the "synthetic control" approach is not applied to corporate bonds and equities data due to smaller cross-section making the approach infeasible.

1 Related literature

There is currently an active research agenda studying how the ongoing climate change affects asset prices. Broadly speaking, climate change risk can materialize through two distinct channels, usually referred to as "transition" and "physical" risks.[7]

First, as climate change intensifies, governments may impose stricter regulations on carbon emissions, hurting the profitability of carbon-intense companies, a key form of transition risk. Consistent with this channel, Bolton and Kacperczyk (2021, 2023) find that companies with higher CO_2 emissions have higher historical returns than companies with lower emissions. Ilhan et al. (2021) use options data to show that more carbon-intensive firms have greater downside tail risk. In corporate bond markets, Seltzer et al. (2020) show that after the 2015 Paris Agreement, the credit ratings and yield spreads reacted more for highly polluting firms than for the lesser polluting ones. Sautner et al. (2023) highlight that shocks to upside opportunities associated with climate change may also affect risk premia, and indeed find evidence consistent with this hypothesis.

The second climate risk is due to exposure of physical assets to the negative consequences of climate change. As climate change intensifies, extreme events such as hurricanes, wildfires, heat waves, droughts, and floods are expected to become more frequent and intense. Furthermore, rising sea level may lead to permanent destruction of coastal assets such as real estate. Indeed, Bernstein et al. (2019) and Baldauf et al. (2020) find a negative relation between exposure to rising sea level and house prices in the U.S. However, Murfin and Spiegel (2020) find no significant relation with a relatively tight upper bound. In municipal bond markets, Painter (2020) finds that bonds issued by large coastal counties with more exposure to rising sea level have higher yields compared to bonds issued by less exposed municipalities. This difference is concentrated on long-term bonds with no evidence for differences in yields for short-term bonds. Goldsmith-Pinkham et al. (2023) also find such a relation but with

[7] Since we cannot possibly do full justice to the rapidly expanding literature on these risks, see Acharya et al. (2023) for a more comprehensive summary.

significantly smaller magnitude. Correa et al. (2021) find evidence that changes in hurricane risk exposure affect corporate loan spreads. Hong et al. (2019) find that the stock prices in food industry react only slowly to projected increases in drought exposure.

Similar in spirit to this second strand of papers, our paper too focuses on physical climate risk but specifically on heat stress risk. Relatedly, Bansal et al. (2021) use changes in the long-run historical temperatures as a measure of overall climate change intensity, and show that stocks whose returns are more negatively correlated with the measure have earned higher returns than stocks with less negative correlation. They also provide evidence that the premium is substantially due to physical, not transition, risk. We broaden the focus by studying multiple asset classes, especially municipal and corporate bonds, by exploiting measures of their local heat stress exposure rather than just sensitivity to aggregate temperature shocks or trends.

Another strand of asset pricing papers related to climate change includes Engle et al. (2020) who propose news-based measures to create climate change hedging portfolios, and several other papers that have followed building and exploring asset-pricing implications of news-based climate risk measures; Hong et al. (2020) and Giglio et al. (2021) provide more recent, comprehensive reviews on the current status of this research agenda. Alekseev et al. (2022), in particular, focus on local heat shocks (injuries or fatalities, high crop indemnity payments, and 10-year record of average quarterly temperatures) to construct hedging portfolios for these news-based climate change measures. Their approach, which is to rely on rotation in trading quantities of equities by mutual funds exposed to these shocks, is complementary to ours, which relies on direct measures of issuers' exposures to physical climate risks including heat stress. Furthermore, we focus directly on the impact of physical climate risks on the cross-section of asset prices and expected returns in bond and equity markets.

2 Data

2.1 Heat (and other physical climate) exposure data

To measure physical climate exposure, we use two complementary data sources. First, Hsiang et al. (2017) develop the Spatial Empirical Adaptive Global-to-Local Assessment System (SEAGLAS) to estimate economic damages from climate change in the United States at county-level for various hazards, such as increase in energy expenditures and decrease in labor productivity (separately for industries with high and low exposure to outdoor heat). We provide below some of the details as to how they obtain these damage estimates. They first construct probabilistic projections of daily temperature and precipitation changes under different RCP ("Representative Concentration Pathway") scenarios using 44 existing climate models and model surrogates from Rasmussen et al. (2016) at a weather station level. RCP 8.5, for example, refers to the concentration of carbon that delivers global warming at an average of 8.5 watts per square meter across the planet. The RCP 8.5 pathway delivers a temperature increase of about 4.3°C by 2100, relative to pre-industrial temperatures. Each county is then assigned station-level projections from the nearest to their geographic centroid.

In the spirit of Hsiang et al. (2017), we construct our first and simplest heat exposure measure – Δ Proj Hot days – as the change in the projected number of hot days per year (days with maximum temperature +100°F) between 2080-2099 and the baseline year 2012 under the "business-as-usual" (RCP 8.5) climate change scenario, using the average projection of the 44 climate change models. This variable directly measures how heat wave frequency is expected to increase in different counties if we fix the future path of global carbon emissions to a relatively pessimistic level.

Figure 2 illustrates how Δ Proj Hot days is constructed. It plots the projected annual temperature distributions for selected pairs of cities, both for 2012 baseline and RCP 8.5 scenario between 2080-2099.[8] Comparing Orlando and Miami, for example, we see that

[8] Note that 2012 distributions are not based on actual temperature data, but instead model-implied distributions if we fix global greenhouse gas concentrations to this baseline level.

neither city is currently experiencing any hot days on average, but the frequency of such days is expected to increase significantly more for Orlando than for Miami, with Orange and Miami-Dade counties being in 74th and 26th percentile among all U.S. counties in terms of the projected increase in the number of hot days, respectively. For all cities, Δ Proj Hot days is the difference in the area above +100°F threshold between RCP 8.5 and Baseline scenarios.

Next, Hsiang et al. (2017) transform these temperature projections into economic impacts using hazard-specific dose-response functions. For energy impacts, this is done using National Energy Modeling System (NEMS), that is developed by the U.S. Energy Information Administration and used to model energy supply and demand across different regions of the U.S. The model is used to project changes in residential and commercial energy expenditures as a response to changes in daily temperatures (in particular, changes in heating and cooling degree days (HDD, CDD)). Impact of changes in daily maximum temperatures on labor productivity is derived using a dose-response function from Graff Zivin and Neidell (2014). Note that these transformations use information about the shift in the whole temperature distribution instead of just changes in the number of hot days, although we later find that this right tail explains most of the cross-sectional variation in heat-related damages.

The damages that Hsiang et al. (2017) estimate are generally expressed as percentages between RCP 8.5 and a counterfactual scenario where further climate change does not occur after 2012. For example, SEAGLAS estimates suggest that by the late 21st century, energy expenditures in Orlando will be 13.8% higher due to the climate change compared to a counterfactual scenario with no climate change, providing a scale-free intensive measure for climate change damages for this particular hazard. Similarly, for Orlando, the estimates suggest that labor supply in industries where workers are heavily (minimally) exposed to outdoor temperatures will decrease by 2.5% (0.5%) as a direct consequence of climate change.

Following methodology similar to theirs, we convert these scale-free measures into dollar damages using state-level data on labor compensation by industry from Bureau of Economic

Analysis (BEA), and energy expenditures from the U.S. Energy Information Administration (EIA). More precisely, to get dollar energy damages per capita per year in county c, we multiply state-level energy expenditures per capita with Hsiang et al. (2017) damage projections for county c, essentially assuming that energy expenditures per capita are constant across the state:

$$\text{Energy dmg per capita}_{c,s} = \frac{\text{2019 Energy expenditures}_s}{\text{Population}_s} \times \text{Energy expenditures (\% change)}_c. \tag{1}$$

Similarly, we use lost wages as a measure of economic damages related to decrease in labor productivity. We first calculate at state-level the total dollar compensation that employees in high-risk industries were paid in 2019 and convert it to per-capita measure.[9] Then, assuming wages and industry composition are constant across the state, high-risk labor damages per capita per year in county c are:

$$\begin{aligned} \text{High-risk labor dmg per capita}_{c,s} = \frac{\text{Total wages in high-risk industries}_s}{\text{Population}_s} \\ \times \text{High-risk labor productivity (\% change)}_c. \end{aligned} \tag{2}$$

To get damages associated with labor productivity in low-risk industries, we follow a similar procedure, using the total dollar compensation in all non-high risk industries as a state-level measure. Finally, we scale all our measures with 2019 GDP per capita.

One of the main limitations of this measure is that it does not capture all channels through which extreme heat can cause economic damages. For example, extreme heat causes damages to infrastructure (such as roads, bridges, and buildings), the cost of which are not captured by the SEAGLAS measure. Similarly, the measure does not capture any heat-related damages to agriculture or human health. Furthermore, the measure does not account for the

[9] High-risk industries are defined as Farm compensation (NAICS:111-112), Forestry, fishing, and related activities (NAICS:113-115), Mining, quarrying, and oil and gas extraction (NAICS:21), Utilities (NAICS:22), Construction (NAICS:23), and Manufacturing (NAICS:31-33).

compounding effect of humidity on energy expenditures and labor productivity.[10] These limitations likely cause us to underestimate the total damages that heat stress is projected to cause.

On the other hand, there are also limitations that would cause us to overestimate damages. One potentially important source of such measurement error arises from the fact that the SEAGLAS estimates are constructed assuming that the composition of U.S. economy is static over the simulation period, which does not account for within-country migration as a response to climate change or any other adaptation responses that have not already been observed historically. For example, if the cost of electricity production or the labor intensity of outdoor activities would decrease as a result of adaptation investments, the total economic damages of heat stress would be lower than the estimates suggest (see e.g. Kahn and Zhao (2018) for theoretical discussion on the impact of adaptation on climate damages).

To the extent that these limitations have a level impact on projected damages, they cause us to overestimate or underestimate the per-dollar effect of climate damages on asset prices, but otherwise have no impact on our inferences. In contrast, any cross-sectional variation in the measurement error results in the standard errors-in-variables problem, biasing our estimates towards zero.

Our second data source for physical climate damages is Four Twenty Seven, Inc. (427), an affiliate of Moody's. 427 provides risk scores for various entities, such as public companies and U.S. municipalities, by first modeling how exposed different geographical regions are to various climate change related risks, and then attributing these risks to the entities based on their geographical location. In the case of public companies, 427 first creates exposure measures at establishment-level (e.g. production plants and office buildings), and then ag-

[10] We note though that the magnitude of these compounding impacts are considered by some researchers to be relatively minor. For example, Maia-Silva et al. (2020) estimate that accounting for the compounding effect of humidity increases the projected increase in cooling demand from 6.88% to 7.06% for the average state. Similarly, Behrer et al. (2021) find that one additional day with >32 °C lowers annual payroll by 0.046% when accounting for humidity, compared to 0.043% dry-bulb estimate. However, for agricultural losses, this may be different; Haqiqi et al. (2021) show that wet heat is more damaging than dry heat for corn.

gregates these to the company-level to assess the total exposure of a company. The resulting scores are relative measures between 0 to 100, with higher score indicating higher risk exposure. In total, we have data on risk scores in several risk categories: heat stress, water stress (drought), flood (corporations only), extreme rainfall (municipalities only), hurricane, and sea level rise. Throughout the paper we will focus on heat score, but employ these other scores in the final analysis of the paper (See Conclusion and Online Appendix 2.1) when evaluating the asset-pricing impact of heat stress relative to these other physical climate risks.

The main limitation of the 427 measure (and the raw temperature measures) compared to the SEAGLAS measure is its relative nature: we can observe under the 427 measure if one entity is more exposed to heat stress than another one, but we lack any information on economic magnitudes or natural reference points for economic severity implied by the scores. The main benefit, on the other hand, is that because 427 carries out its exposure modeling globally and has establishment-level information on locations of companies' physical assets, their measures account for companies' international establishments in addition to the U.S. ones. To construct a firm-level SEAGLAS measure, we first measure the geographical footprints of U.S. firms using establishment-level data from Dun & Bradstreet Global Archive Files, and then calculate firm-level exposure as the employee-weighted average of the SEAGLAS measure across the counties in which each firm operates.

Another limitation common to both measures is that they are cross-sectional snapshots measured at a single point of time. Hsiang et al. (2017) measures use data up to around 2013, and 427 scores are measured as of December 2019 for corporations and Feb 2020 for municipalities. If the cross-sectional rankings of these exposure measures varied substantially over time, it would introduce measurement error in our x variable that would presumably grow larger the further away we move from the time of measurement. That said, there are several reasons why we are not particularly concerned about this possibility. First, while it is highly plausible that damage estimates are periodically revised as we accumulate more knowledge on the impacts of climate change, spatial variation in the level of heat exposure is likely to dominate any spatial variation in these temporal revisions. In other words, revised damage estimates are unlikely to substantially change the cross-sectional exposure rankings. Indeed, the rank correlation of 2018 and 2019 vintages of 427 scores is 0.999. Second, the two measures we employ yield very similar results for asset prices despite substantial gap in their time of measurement (among many other methodological differences).

Figures 3 (a) and (b) plot the distributions of both our heat exposure measures in the municipality sample. We refer to SEAGLAS measure as "Heat damage" and the 427 measure as "Heat score." The range for annual heat damage is approximately -0.52% to 1.86% of GDP. Negative damages for some municipalities reflect the fact that they benefit from the decrease in the number of cold days (e.g., fewer winter storms) more than they suffer from the increase in hot days. Comparing panels (a) and (b), we can see that overall the two measures (SEAGLAS and 427) agree quite well about the geographical distribution of heat stress exposure, with rank correlation between the two being 0.59. The two measures mainly disagree in which geographic regions are the most exposed: the first assigns south central states as the most exposed, while the second assigns Midwest states as the most exposed.

Figure 3 (c) plots the distribution of our raw measure for projected change in heat wave frequency across the country (Δ Proj Hot days). It is very highly correlated with SEAGLAS measure (0.82), which is perhaps unsurprising given that the latter uses the former as an input. Nonetheless, this high correlation suggests that the main source of variation in SEAGLAS measure comes from the geographical variation in the projected increase in heat wave frequency, instead of any other inputs that SEAGLAS uses to transform these temperature changes into economic damages.

Finally, Table 1 Panel A shows the summary statistics for all our heat stress measures. Each year, an average municipality is projected to suffer damages that equal to 0.83% of GDP. Note that the damages can – and are indeed observed in the distribution to – be negative for some counties as higher temperatures can reduce energy expenditures and raise labor productivity in extremely cold geographies. The raw SEAGLAS measure for the projected change in heat wave frequency (Δ Proj Hot days) suggests that for the average municipality, the total number of extremely hot days per year will increase by 38.16 days by the end of the century, ranging from 0.01 days to 108.48 days.

To assess how our measures relate to measures of heat exposure based in historical temperature data, we add two additional variables. The first temperature measure – Δ Hot days – is the change in the average number of hot days between 2001-2010 and 2011-2020, which attempts to capture recent temperature trends. Assuming that the differences in these (imprecisely measured) temperature trends continue in the future, this measure attempts to capture observed effects of climate change occurred already during our sample period. A hot day is defined as the average number of days per year when the maximum wet bulb temperature (Behrer et al., 2021) in the county was above 100°F. Using this historical measure, the number of hot days for average county increased by 0.67 days per year, ranging from -8.8 days to 27.40 days.[11] The second historical temperature measure – Past Hot days – counts the average number of heat disaster days in the county over a rolling 3-year window according to the data from SHELDUS. This measure attempts to capture the realized heat stress exposure of a county, given that SHELDUS records any observed severe events that caused significant damages or fatalities. Figures 3 (d) and (e) plot the distributions of Δ Hot days and Past hot days across the U.S.

Table 1 Panel B shows the rank correlations of our risk measures. The wet-bulb temperature measure is positively rank-correlated with SEAGLAS and 427 risk measures (0.35 and 0.40 for Heat damage and Heat score, respectively), suggesting that our measures are indeed related to cross-sectional variation in temperature trends. That said, the relatively modest correlations between historical temperature measures and measures based on future

[11]Note that the distribution of Hot days shows that more than 25% of the counties did not have any days during 2011-2020 with maximum wet bulb temperature above 100°F; similarly, Δ Hot days shows a reduction in the Hot days over the past decade for some counties. These distributional features of regional heat stress outcomes in historical data are not reflected in the distribution of Δ Proj Hot days given the severe heat stress scenario projection of SEAGLAS.

projections also suggest that using historical temperature data to proxy for future changes would likely introduce significant amount of measurement error. This distinction is potentially important, since Addoum et al. (2020) find little evidence that historical temperature shocks have impact on establishment-level sales in the U.S. Past realized heat disasters from SHELDUS has surprisingly low correlation with SEAGLAS and 427 risk measures, which is also evident when comparing Figure 3 Panel (a) and (b) to Panel (e). This is mainly due to the fact that historical heat disasters are surprisingly evenly distributed across the country, likely due to exposure to hot weather being positively correlated with adaptation efforts: a similarly severe temperature event is likely to cause larger damages in the north where the society is less resilient to such events due to their rarity. This low correlation also suggests that past realized heat damages are unlikely to be a confounding factor for our climate change exposure measure, though we will control for them directly.

Finally, Table 1 Panel C shows the summary statistics of the geographically-aggregated SEAGLAS measure and the 427 score for heat stress exposure at company-level. On employee-weighted basis, the average company resides in a county that is projected to suffer damages that equal to 0.71% of GDP each year due to increase in heat-related issues. Note that compared to the county-level sample, the variation in exposure is somewhat lower for companies due to their geographic diversification.

Next, we describe the municipality and company level data sets that we merge with our exposure data to analyze the impact of heat stress on cost of capital.

2.2 Municipal bonds

Our two main data sources for municipal bonds are Mergent Municipal Bond Database for bond characteristics and ratings, and MSRB's Municipal Securities Transaction Data for secondary market prices. We begin by selecting from Mergent data fixed-coupon, tax-exempt bonds with no insurances (since bonds with insurances do not properly reflect the issuer-specific credit risk). Next, we match these observations to the physical risk exposure data. Since our climate exposure variables are available at municipality-level, we need to determine which geographical area a given issuer is associated with. To do so, we match issuer names with state, county, and place names in the Census geocode file. The details of this procedure are provided in the Online Appendix 1. The algorithm described therein allows us to find the geographical location for more than 90% of individual bonds in the Mergent database. The rest are matched by hand. At this point, we exclude any state-issued bonds because their climate risk exposure cannot be directly mapped to our county-level exposure measures.

Next, we construct our secondary market yield variable following Green et al. (2010) and Schwert (2017). In particular, we first exclude any bonds from MSRB data that have fewer than 10 trade observations to ensure a minimum level of trading liquidity. Furthermore, we exclude trades that occurred during weekends or holidays, and filter any observations with time to maturity of more than 100 years, coupon rate more than 20%, or a price lower than \$50 or greater than \$150 (on a \$100 notional) as likely data errors. Finally, we exclude bonds during the first three months after the issuance and during the last year before maturity, because newly issued bonds and bonds close to maturity may exhibit underwriting support, a pull-to-par effect, and/or a high level of price dispersion, making these observations particularly noisy for robust econometric analysis.

Because municipal bonds trade infrequently and intra-day prices can fluctuate quite a lot depending on the type of the transaction (customer buying, customer selling, inter-dealer trade, etc.), we measure daily "fundamental prices" as the average of the highest customer sale price and the lowest customer purchase price. If these two prices are not available, we use average inter-dealer trade price instead. Following Goldsmith-Pinkham et al. (2023), we use maturity-matched Municipal Market Advisors' AAA-rated yield as a tax-exempt benchmark rate to convert yields to credit spreads. Then, we convert the spreads to monthly frequency by using the most recent available observation in a given month. Finally, we exclude bonds after redemptions (e.g., due to advance refundings), and require that each bond-month observation is associated with at least one outstanding credit rating from S&P, Moody's, or Fitch.

Other data sources in our analysis include the U.S. Energy Information Administration's State Energy Data System (SEDS) for state-level annual energy expenditures per capita, the Bureau of Economic Analysis' Regional Database for county population and income per capita, the Bureau of Labor Statistics' Local Area Unemployment Statistics Data for county-level unemployment, the U.S. Census' Annual Survey of State and Local Government Finances (Pierson et al., 2015) for local government debt-to-revenue,[12] Spatial Hazard Events and Losses Database for the United States (SHELDUS) for historical heat disasters, and the county-level fossil fuel exposure measure of Raimi et al. (2022).

Table 2 Panel A provides the summary statistics for our final sample. After removing negative credit spread observations and trimming the right tail at 2.5% level, the average credit spread in our sample is 69 bps. Time to maturity ranges from 1 year to 50 years, with the average being approximately 12 years. We convert credit ratings into numerical values with smaller numbers indicating higher ratings (1=AAA/Aaa, 19=D/C) and take the average across available ratings issued by these different agencies (rounded to the nearest integer). The average rating score in our sample is around 4, which corresponds to AA- for S&P and Fitch, and Aa3 for Moody's. Finally, while general obligation bonds are the most common type of bonds issued, in our sample they consist only of 35% of all observations.

2.3 Corporate bonds

Our corporate bonds sample is constructed using Mergent FISD and WRDS Bond Returns databases. We use USD denominated, non-144A, nonconvertible, senior unsecured bonds with more than $100,000 offering amount and more than three months since issuance and more than one year to maturity. To measure credit spreads, we subtract maturity-matched Treasury yield from a bond's end of month yield to maturity.[13] We measure bond turnover

[12]To calculate county-level debt-to-revenue, we sum up total revenue and total debt outstanding for all government entities in a given county, using the most recently available figures for each entity.

[13]Note that we use different measures for risk-free rate in municipal bond and corporate bond samples due to differences in asset class-specific conventions. Results go through if we use maturity-matched swap rates

as the total par-value volume over the past 12 months divided by the offering amount.

Table 2 Panel B summarizes our sample. After removing negative credit spread observations and trimming the right tail at 2.5% level, the average credit spread in our sample is 156.9 bps. Time to maturity ranges from 1 year to 100 years, with the average being approximately 10 years. The average rating score is around 7, which corresponds to A- for S&P and Fitch, and A3 for Moody's. Compared to our municipal bond sample, corporate bonds on average have higher spreads (157 bps vs 69 bps), lower credit ratings (A- vs AA-), and substantially higher turnover (63% vs 3%). The average time to maturity is similar in both samples.

2.4 Equities

While the standard methodology in the empirical asset-pricing literature is to use realized returns as a measure of *ex-ante* expected returns, this approach is problematic in our setting since a primary hypothesis under investigation is that expected returns may have changed during our sample period. Moreover, Pástor et al. (2022) have argued strongly, based on evidence in Ardia et al. (2020), that unexpected increases in climate change concerns, rather than risk premia, were responsible for the out-performance of environmentally sensitive stocks during 2010-2018.[14]

To overcome this problem, we follow Martin and Wagner (2019) and construct a measure for conditional expected return at the stock level that uses only forward-looking information. In particular, we use OptionMetrics IvyDB US to obtain implied volatility surfaces and stock prices for individual companies and the S&P 500 index. We use maturity-matched Treasury zero coupon yield as a measure of the risk-free rate. The yield curve is constructed by interpolating over the rates available in OptionMetrics. We annualize the most recently

as risk-free rates in both markets instead.

[14]Since the climate risk measures we employ are restricted to constituents of the S&P 500 in 2019, another set of concerns about using historical returns to measure expected returns stems from a potential survivorship bias because the sample firms are likely to have experienced a series of positive shocks that resulted in them being added to the S&P 500. While our estimation strategy sidesteps this concern, our results remain similar if we restrict the sample to companies that were constituents of the S&P 500 throughout the sample period.

paid dividend to measure dividend yield, essentially assuming that the dividend yield stays constant throughout the life span of an option. After converting implied volatilities to option prices using the Black-Scholes formula, we calculate the risk-neutral volatility for stock i at the end of month t as follows:

$$SVIX_{i,t}^2 = \frac{2}{R_{f,t+1} S_{i,t}^2} \left[\int_0^{F_{i,t}} \mathrm{put}_{i,t}(K) dK + \int_{F_{i,t}}^{\infty} \mathrm{call}_{i,t}(K) dK \right], \tag{3}$$

where S is the price of the underlying stock (or index), R_f is the gross risk-free rate, F is the forward price of the underlying (strike price at which call and put prices are equal to each other), $\mathrm{call}_{i,t}(K)$ and $\mathrm{put}_{i,t}(K)$ are put and call prices with strike price K.

Building on the logic of Martin (2017), Martin and Wagner (2019) show that under some assumptions (reviewed below) the expected excess return on stock i can be approximated by a combination of three components: (i) $SVIX_i$; (ii) analog of $SVIX_i$ for the value-weighted market portfolio, $SVIX_m$; and, (iii) the value-weighted average of $SVIX_i$ across all the stocks in the market portfolio, $\overline{SVIX}$. Specifically, the dependent variable in our stock market regressions is

$$E_t(R_{i,t+1}^e) = R_{f,t+1}(SVIX_{m,t}^2 + \frac{1}{2}(SVIX_{i,t}^2 - \overline{SVIX}_t^2)). \tag{4}$$

Martin and Wagner (2019) provide extensive evidence supporting this measurement strategy, which has also been used by Lee et al. (2021) and Pagano et al. (2023). Note that the computation of this estimator does not involve any auxiliary free parameters. The key assumptions of the approximation are: first, that in the sample of stocks being studied, the range of betas from a projection of returns on that of a hypothetical "growth optimal" portfolio is not too wide; and, second, that the variance of the residuals for each stock is not persistently different from the value-weighted average. The applicability of these assumptions is likely to be more valid in the cross-section of S&P 500 stocks than in broader cross-sections of asset markets. We check the robustness of our results by further restricting the sample based on the range of estimated second moments. In our application, it is worth noting that we do *not* rely on the stronger assumptions in Martin (2017) that identify the market risk premium with $SVIX_m^2$ because our specifications are purely cross-sectional and include time fixed effects.

Table 2 Panel C provides the summary statistics of this expected return measure for our sample of U.S. equities. After removing a few observations with negative expected excess returns and trimming the right tail at the 2.5% level, the average annualized expected excess return is 452 bps. In some of our specifications, we control for stock characteristics underlying the Fama-French 5-factor model and momentum; these characteristics are also summarized in the panel.

3 Empirical approach and results

3.1 Municipal bonds

3.1.1 Strategy 1: Rating x Year fixed effects and Oster (2019) bound

As seen in Figure 3, the spatial variation in our heat risk measures is driven primarily by the geographic locations of municipalities. As a consequence, a challenge we face is that local economic conditions also vary spatially across the country, affecting creditworthiness of bond issuers and hence the credit spreads of their bonds. As stressed by Goldsmith-Pinkham et al. (2023), controlling for such local conditions is crucial to identifying a link between credit spreads and damages related to climate change.

One established identification strategy in a case like this is to rely on spatial discontinuities in risk exposure. For example, Goldsmith-Pinkham et al. (2023) compare bonds issued by different school districts in the same county to control for local economic conditions, and finds that bonds issued by coastal districts that are exposed to sea level rise have higher credit spreads compared to bonds issued by non-coastal districts. In our case of heat risk exposure, exploiting such spatial discontinuities is unfortunately not feasible. Temperature by its very nature changes only gradually across locations unlike many other physical climate risks, which is apparent by comparing Panel (b) of Figure 3 and (d) of Figure A1: while the rank correlation in sea level exposure scores among pairs of adjacent municipalities is only 0.283, it is 0.978 for heat stress. This implies that adjacent counties are very similarly exposed to heat waves making any discontinuities virtually nonexistent.[15]

Instead, our empirical strategy builds on the following observation: *historically, physical climate risks have had limited impact on credit ratings.* This is stated perhaps most explicitly in a 2015 white paper by Moody's that discusses how environmental risks are assessed during a credit rating process:

> *Based on currently limited visibility into the nature, probability, and severity of the follow-on risks to a global warming trend (e.g., droughts, floods) – combined with an extremely long projected time frame – direct climate change hazards are not at present a material driver for ratings.*
>
> "Moody's Approach to Assessing the Credit Impacts of Environmental Risks"
> Moody's Investors Service (2015)

Notwithstanding this limited visibility, all the major credit rating agencies have recently updated their rating criteria documents to discuss the role of climate risks in their rating frameworks more thoroughly. For example, S&P Global Ratings published a new white paper in October 2021 that describes the principles through which Environmental, Social and Governance (ESG) considerations are taken into account when assessing creditworthiness of various bond issuers (S&P Global Ratings, 2021). Among various ESG factors, *"climate transition risk and physical risk-related factors may be among the most significant ESG credit factors that affect the creditworthiness of rated entities"*, highlighting the potential impact of physical climate risks on the cash flows of issuers.[16]

[15] One potential counterargument to this conclusion is that while the average pair of municipalities is less likely to differ in terms of heat stress exposure than sea level exposure, the sample size for the former is larger because comparing sea level risk exposure only makes sense if one of the two counties is coastal. The conclusion is similar when comparing the sample sizes where the risk exposure between adjacent counties differ by more than 20 points in the 427 measure: with sea level exposure, the number of such pairs is 587 but only 9 for heat stress.

[16] See Moody's Investors Service (2020) and Fitch Ratings (2021) for similar assertions in white papers

Despite the prominent role of physical climate risks in the revised framework, these risks have only resulted in an extremely limited number of credit rating actions to date, generally as a response to a materialized climate event. This is mainly due to the fact that in addition to being material, S&P for example requires that it has "sufficient visibility and certainty" on an ESG factor to include it in the credit rating analysis. Given that the envelope of uncertainty around various climate scenarios and their impact on the economy is extremely large, it is understandable that forward-looking physical risks typically do not meet the criteria for a credit rating impact.[17]

This observation that credit ratings have not historically reflected physical climate risks enables us to add flexible credit rating fixed effects to our specification to control for "traditional" risks affecting creditworthiness that credit rating models are built to capture. Given the detailed nature of the credit rating process, we believe that this approach allows us to control for a vastly superior set of issuer-level confounding factors affecting creditworthiness than any set of controls that is directly available to an econometrician. Given this approach, the assumption that allows us to identify the impact of heat stress exposure on credit ratings is that there are no major risks omitted from credit models that are correlated with heat stress exposure.[18] We furthermore explicitly add flexible time-varying controls for two related but distinct climate-related explanations: first, we control for historical heat disasters from SHELDUS to mitigate concerns that our results are driven by historical events rather than investors' expectations on future events. Second, we use county-level fossil fuel exposure measure of Raimi et al. (2022) to control for climate transition risk.

While credit ratings (and other controls) allow us to directly control for potentially confounding risk factors in principle, they are an imperfect proxy for issuers' creditworthiness in practice. Oster (2019) develops a methodology to evaluate the potential impact of omit-

from the other agencies.

[17]See Barnett (2023) for formal treatment of the effect of climate model uncertainty on asset prices.

[18]Note that the assumption that credit ratings have not historically reflected physical climate risks is to some extent testable: if it was false, controlling for credit ratings should absorb variation in credit spreads that is related to heat stress, displacing our coefficient of interest. This is not the case though: there is little change in our coefficient estimates when credit rating fixed effects are added to the specification.

ted variable bias on coefficient estimates based on coefficient stability after the inclusion of controls. The methodology is applicable in a setting where selection on observables is informative about selection on unobservables, for example when the set of potentially confounding factors is known but only incomplete proxies are available.

Oster's approach seems particularly well-suited for our setting, because the set of potentially confounding factors is heavily guided by asset pricing theory: the main determinant of credit spreads is issuers' creditworthiness linked to partially observable risk factors. Credit ratings are designed to directly measure such creditworthiness, but due to their discrete nature and any potential biases (both documented and undocumented), it is likely that some unobserved differences in credit quality exist even after controlling for ratings. Using the bounding argument of Oster (2019), we can assess how important these unobserved risk factors would need to be relative to the captured factors in order to explain our results.

Results To study the relation between heat stress exposure and credit spreads on municipal bonds, we estimate the following regression:

$$Spread_{b,c,t} = \gamma_c + \gamma_t + \sum_{y=2007}^{2020} I_y \left[\alpha_y Risk_c + \theta_y Z_{b,c,t}\right] + \theta X_{b,c,t} + \varepsilon_{b,c,t} \tag{5}$$

where $Spread_{b,c,t}$ is the credit spread during month t of bond b whose issuer is located in county c. I_y are year dummies, so the coefficients of interest α_y estimate year-by-year sensitivity of credit spreads to heat stress exposure, relative to a baseline year of 2006. Control variables in Z and X include the logarithm of the bond's time to maturity, issuer's option to call a bond before maturity, flag for general obligation bonds, bond turnover, standard deviation of transaction prices for bond b in month t, state-level energy expenditures per capita, county population, income per capita, unemployment, local government debt-to-revenue, the number of heat disaster days over the past 3-year rolling window, fossil fuel exposure measure of Raimi et al. (2022) and – most importantly – credit-rating fixed effects. We also include county and time fixed effects. Standard errors are double clustered by year-month (t) and county (c).

Results are shown in Table 3. The first two columns contain results for SEAGLAS Heat damage measure with and without credit rating fixed effects and other controls. The last two columns repeat the analysis for 427 Heat score measure. The table reveals several interesting patterns. First, while there is little (or at best weak) evidence that exposure to heat stress affects credit spreads during the first half of our sample, a gap between high and low exposure bonds starts to emerge around 2013. This coincides with a time period when attention towards climate change became permanently elevated (see, e.g., discussion in Goldsmith-Pinkham et al., 2023). In terms of economic magnitudes, our point estimates for 2019 suggest that a bond whose issuer is located in a county that is expected to suffer damages that equal to 1% of GDP as a direct consequence of heat stress exposure has a 19.01 bps higher credit spread compared to a case with no climate risk exposure. Based on our second (427) measure, one standard deviation increase in heat stress exposure increases spreads by 8.03 bps. Given that the standard deviation of our first measure is 0.39, the magnitudes of the estimates appear to be consistent between the two measures.

Finally, adding credit rating fixed effects and other controls to our specification has little impact on our coefficient estimates, which is what we expect if credit ratings have indeed not reflected physical climate risks historically. Including the controls substantially increases the explanatory power of the regression. This increase, combined with the observed coefficient stability, is a widely-used diagnostic to bound the effect of omitted variables. We calculate Oster (2019)'s δ for our coefficient estimates (under the most conservative assumption that a theoretical maximum $R^2 = 1.0$ is achievable), and find that its average value between 2013 and 2020 is 1.9 and 1.0 for SEAGLAS and 427 measures, respectively. This implies that in order for any hypothetical omitted variable to explain our results, it would need to be 1-2 times as influential for credit spreads as the factors captured by credit ratings and other control variables that we include. We find such possibility unlikely, given that an extensive empirical literature on determinants of municipal bond yields has not uncovered such factors.

Table A1 shows the coefficients on the following control variables: past heat disaster days, energy expenditures per capita, and fossil fuel exposure measure of Raimi et al. (2022). Our main results are indeed robust to adding these controls, suggesting that past heat disasters, past exposure to energy prices, or climate transition risk does not explain our results.

3.1.2 Strategy 2: Matching ("Synthetic Control")

We then develop and present results for an alternative specification to estimate the effects of heat stress on municipal bond spreads using a matched sample approach. First, we define bonds in the top quintile in terms of heat stress exposure as "treated" bonds, and match them to "control" bonds in the lowest quintile in terms of heat stress exposure.[19] Matching is done among bonds in the same year-credit rating by minimizing the Euclidean distance among covariates proxying for interest rate risk exposure and local economic conditions. In particular, we follow Auh et al. (2022) and perform matching by (standardized) coupon rate, time to maturity, county population, income per capita, and unemployment rate.[20] Panel A of Table 4 shows the average covariates between treated and control samples. The approach generates wide spread in heat risk exposure, while keeping other covariates reasonably balanced.

We then calculate the difference in maturity-matched credit spreads between matched bonds ($\Delta Spread_{b,c,t}$), and regress them on year dummies using the following specification:

$$\Delta Spread_{b,c,t} = \gamma_c + \sum_{y=2007}^{2020} \alpha_y I_y + \varepsilon_{b,c,t}. \tag{6}$$

Results Panel B of Table 4 shows the results. For both heat stress measures, results are similar to the main estimates in Table 3: higher exposure to heat stress is associated with higher credit spreads during the second half of our sample.

Table 5 repeats the main analysis for various subsamples of bonds. We find that the result is mainly coming from bonds with long time to maturity (10+ years), bonds with

[19]Our results are largely unchanged if we use, e.g., 30 and 70 percentile cutoffs instead.

[20]Results are similar if focus only on bond-level covariates used as controls in our main specification instead of the county-level covariates.

below average credit rating (AA- or worse), and revenue-only instead of general-obligation bonds. These results are sensible, as climate risk exposure is likely to more adversely affect municipality/utility cash flows at longer horizons, particularly those from weaker credit municipalities/utilities. Moreover, revenue-only bonds issued by competitive enterprises and utilities lack the credit-enhancement support provided by tax collections backing general-obligation bonds.

3.2 Corporate bonds

Next, we turn our attention from municipal bonds to corporate bonds. We continue to use credit ratings to control for the impact of unobserved non-climate factors that affect firms' creditworthiness. More specifically, we estimate the following regression:

$$Spread_{b,i,t} = \gamma_i + \gamma_t + \sum_{y=2007}^{2020} I_y \left[\alpha_y Risk_i + \theta_y Z_{b,i,t}\right] + \theta X_{b,i,t} + \varepsilon_{b,i,t} \tag{7}$$

where $Spread_{b,i,t}$ is the credit spread during month t of bond b issued by firm i. The coefficients of interest α_y estimate year-by-year sensitivity of credit spreads to heat stress exposure, relative to a baseline year of 2006. Control variables in Z and X include logarithm of the bond's time to maturity, issuer's option to call a bond before maturity, bond turnover, standard deviation of transaction prices for bond b in month t, employee-weighted average number of heat disaster days in the counties in which the firm operates over a rolling 3-year window, industry fixed effects (2-digit SIC code) and credit-rating fixed effects. We also include firm and time fixed effects. Standard errors are double clustered by year-month (t) and firm (i).

Results are shown in Table 6 Panel A. In the full sample, we find a pattern that is qualitatively similar to the one we find for municipal bonds: the difference in spreads between high and low exposure firms increases in the second half of the sample. However, the statistical and economic significance of these results is weak in the overall sample. The results are, however, much stronger when we split the sample into "high rating" (investment grade) and "low rating" (non-investment grade) bonds. For non-investment grade bonds, one percentage point increase in heat related damages increased credit spread by around 38 to 51 bps when using the SEAGLAS measure, and one standard deviation in an issuer's heat stress is associated with an increased credit spread of 33 bps to 53 bps using 427 measure.

In Table 6 Panel B, we repeat Oster (2019) analysis for the low rating bonds. Again, average Oster (2019)'s δ for our SEAGLAS coefficient estimates is 7.3 (3.4 without the unusually high 2020 coefficient), implying that in order for an unobserved covariate to explain our results, it would need to be significantly more influential for credit spreads than the factors captured by credit ratings and other control variables. For 427 measure, our ability to rule out the effects of alternative confounders is significantly weaker, not surpassing the critical value of 1.

Next, we present some important additional results for corporate bonds. We obtained data on expected default frequency (EDF) from Moody's KMV. As EDF reflects a mapping from a Merton-model implied distance-to-default into a physical or statistical probability of default for the firm, EDF can be considered as capturing the cash flow risk to the corporate bond.[21] Given EDF naturally affects credit spreads up to a risk premium multiplier (and a loss given default), we ask if the credit spread exposure to heat stress is associated with a separate (climate) risk premium or not, i.e., a risk premium over and above that of the expected cash flow risk. This distinction is particularly important because it is not *a priori* clear whether the climate risk premium should be positive or negative as different macroeconomic models of climate change make different predictions on the sign of the premium. It is also possible that the premium could be zero if climate risk is viewed as purely idiosyncratic and diversifiable.

To this end, in Table 7 we regress credit spreads of low-rated corporate bonds on heat

[21] More specifically, the future distribution of market value of assets is first calculated using Merton-model using current market value and volatility of a firm's equity and its leverage. Then, firm-specific cumulative default probability is estimated based on a mapping from the implied "distance to default" to historical default frequencies. Ten year EDF, for example, then represents the annualized probability of default in the next 10 years.

stress exposure controlling for EDF:

$$Spread_{b,i,t} = \gamma_i + \gamma_t + \sum_{y=2007}^{2020} I_y \left[\alpha_y Risk_i + \beta_y EDF_{i,t} + \theta_y Z_{b,i,t}\right] + \beta EDF_{i,t} + \theta X_{b,i,t} + \varepsilon_{b,i,t}. \quad (8)$$

Under this specification, coefficients on EDF (β_y) should capture the impact of average source of default risk on spreads both through its impact on expected losses and a (multiplicative) risk premium; in particular, expected losses embed the cash flow effects of heat stress exposure under rational expectations of likely bond market investors. The coefficients on heat stress (α_y), on the other hand, capture whether the risk premium on (cash flow effects due to) heat stress exposure is higher, lower, or the same, as the premium on the overall default risk.

We observe in Table 7 that the coefficients on SEAGLAS heat damage measure are on average positive after 2010 in the low rating sample, controlling for EDF which also carries positive year-by-year coefficients. We interpret this result as the risk premium in low-rated corporate bonds on heat-stress related climate damages being of a similar order of magnitude until 2010 and higher after 2010 as the risk premium on the non-climate cash-flow risk. Given that corporate bond spreads are associated with a positive risk premium on average (as seen in the coefficients on EDF), overall these results suggest that the risk premium on heat stress exposure is also positive. Note, in particular, that the effect of firm-level EDF on spreads is in line with a reasonable assumption on loss given default of around 30-60% and rises especially during years of stress such as 2008-09 (global financial crisis), 2012 (European sovereign debt crisis), and 2015-2016 (oil-price crash and Chinese devaluation). For 427 measure, the pattern is qualitatively similar but statistically weaker, with some lack of robustness in the positive sign of coefficients on EDF in moving from the first half of our sample period to the second half.

3.3 Equities

To make further progress in disentangling the price of climate risk from its impact on expected cash flows, we turn our attention to equities, for which we have a direct measure for the conditional expected return or risk premium. To study the relation between expected excess returns and heat stress exposure at firm level, we estimate a regression similar to the one in the case of municipal bonds:

$$E_t(R_{i,t+1}) = \gamma_i + \gamma_t + \sum_{y=2007}^{2020} I_y \alpha_y Risk_i + \theta X_{i,t} + \varepsilon_{i,t}, \tag{9}$$

where $E_t(R_{i,t+1})$ is the annualized one-month expected return on stock i in the end of month t computed using the Martin and Wagner (2019) methodology as described in the previous section. We also use one-year expected returns as an alternative measure. The controls include market beta, size, book-to-market, profitability, investment, and past 12-month returns. We also include firm and time fixed effects. Standard errors are double clustered by year-month and firm. We impose the restriction that the firms' risk-neutral beta is between 0.0 and 2.0, as the approximation in Martin and Wagner (2019) is more suitable for this range[22]. We also impose balanced panel restriction so that we require the firm to be present throughout the sample period.

Results are shown for the SEAGLAS measure in Panel A and for the 427 measure in Panel B of Table 8. Similar to our earlier results for municipal and corporate bonds, there is little evidence that heat stress exposure has an impact on expected returns during the first half of our sample, but an effect becomes detectable after 2015-16. On average, the estimates suggest that a one standard deviation increase in heat stress exposure increases expected returns by around 20 bps, which corresponds to an approximately 10% increase compared to the unconditional mean. Interestingly, this magnitude is similar to the one we estimated for municipal bonds but smaller than that for junk-rated corporate bonds.

[22]In particular, the approximation is valid when β^* is close to one. See Section I of Online Appendix to Martin and Wagner (2019) for more detailed description.

The coefficient pattern is seen to be similar whether we use 1-month or 1-year expected returns as y-variable.[23] Furthermore, the two last specifications follow Doshi et al. (2019) in unlevering equity expected returns to get an estimate of firm expected returns. Since heat stress is associated positively with higher credit spreads, this specification addresses the concern that, rather than picking up a heat stress risk premium, our regressions are picking up an amplification of non-climate related risk premia via leverage. The results suggest this is not the case; S&P 500 companies are not on average highly leveraged, so that while the estimate of unlevered risk premium on heat stress is somewhat smaller than the levered risk premium, it is both statistically and economically significant at around 15 bps, especially since 2015-2016, supporting our overall interpretation.[24]

3.4 Interpreting the heat stress coefficients

3.4.1 Sign of the premium

Different macroeconomic models of climate change make different predictions on the sign of physical climate change risk premium. In models such as Nordhaus and Boyer (2003) and Nordhaus (2008), climate change damages grow with consumption because rapid economic expansion increases carbon emissions. As a result, assets that are highly exposed to physical climate risk act as a hedge against consumption shocks, and as a result are associated with a negative risk-premium. On the other hand, in models such as Weitzman (2012, 2014) and Bansal et al. (2021) climate damages have a direct negative effect on aggregate consumption (e.g. a "climate disaster"), so that consumption is low when climate shock materializes. In such models, marginal utility is high when climate damages are high, and assets exposed to

[23] Given earlier results that physical climate risks seems to affect bond spreads mainly at longer maturities, it would be interesting to study the relation between heat stress and the whole term-structure of expected equity returns. However, this is not feasible due to option expiration dates rarely exceeding a few years.

[24] In a closely related paper, Gostlow (2021) uses the same 427 heat risk measure and finds that more exposed firms have had lower average returns during 2010s. This seemingly contradictory result is in fact fully consistent with ours: if heat risk premium emerged during this time period as our results suggest, we should indeed observe their realized performance to be muted as the risk premium increased (e.g. Pástor et al. (2022)).

such damages carry a positive risk-premium. This distinction has important implications for the profitability of climate abatement investments today, since the discount rates applied to such investments are low under the second class of models compared to the first one.

Our results are more consistent with the second class of models, since find that the conditional expected returns on stocks more exposed to increase in heat stress is higher by 20 for damages equaling 1% of GDP. This suggests that investors are worried about states of the world where climate damages are high, and demand a risk premium for assets exposed to such risks. Consequently, any climate change adaptation investments that companies may undertake are discounted with lower rates, making more such investments NPV positive.

3.4.2 Magnitude of the premium

Next, we will discuss the magnitude of our coefficient estimates across the asset classes. For municipalities, local exposure to increased damages related to heat stress equaling 1% of GDP is associated with municipal bond yield spreads that are higher by around 25 bps per annum compared to a counterfactual scenario where these damages would not increase due to climate change. For corporate bonds, the effect is around 45 bps for sub-investment grade corporate bonds, with little effect for investment grade bond spreads.

Climate damages affect these yield spreads both through the cash flow channel (higher probability of default and/or loss given default), and risk premium (that could be positive or negative as discussed in the previous subsection). Given that we find 25 bps per annum effect on conditional expected returns on equities (that only reflects the discount rate channel), it is likely that the 45 bps effect on corporate bonds reflects both compensation for increased expected losses, and a positive risk premium associated with such losses.

3.4.3 Time series evolution of the premium

The increasing risk premium on heat stress exposure over time across municipal bonds, corporate bonds, and equities could be due to an increase in the risk itself (as perceived by investors), an increase in required compensation for that risk, or both. On the first channel, note that for highly asymmetric loss distributions, an increase in the *level* of the expected loss typically also means an increase in *uncertainty* about it. Thus our results are consistent with a recent increase in global mean temperature forecasts, which bring with them an increased likelihood of catastrophic heat scenarios. The second channel could be operational even without an increase in risk, however. Investors could be requiring increased compensation because of a greater awareness of the risk or a heightened appreciation of its systematic nature.

The period since 2013 also coincides with a dramatic increase in environmentally active (ESG) investing and interest in sustainable finance. We do not view that rise as a compelling explanation for our findings which pertain to physical climate risk. Firms and municipalities unfortunate enough to be most exposed to heat stress are not "not green" *per se* and are thus not (to our knowledge) explicitly avoided by ESG investors.

Finally, a caveat is in order in interpreting our results as showing that something has changed since 2013-2015. While it is possible that heat stress risks were lower prior to 2013, or that they were not and investors simply ignored them, our evidence – due to data limitations – is based only on a handful of years. That is, we cannot rule out that heat stress exposures *were* priced before 2006. We simply have no evidence on this point; going farther back in time would ideally require measures of heat stress closer to those dates whereas our measures are using data as of 2013 (SEAGLAS measure) and 2019-2020 (427 measure).

4 Conclusion

Understanding how asset markets price climate risk is important for gauging the private incentives for issuers to respond to the threat, e.g., by undertaking investment in abatement technologies. The magnitude of the market's expected losses and required compensation for risk can also be important inputs to structural models of the broader economic consequences of global warming. Our paper examines the impact of an important physical climate risk – i.e. heat stress exposure – on financial asset prices. We study its effects across three broad asset classes, i.e. municipal bonds, corporate bonds, and equities, providing insights into the impact of climate risk on asset prices at the aggregate level.

Using two complementary data sets for local heat stress exposure, we document empirical evidence for a significant effect of heat stress on prices across the three distinct asset classes. We show that heat stress is priced in both municipal and corporate credit spreads. The price effects in the municipal markets are mostly driven by relatively lower credit quality municipal bonds. The results are sharper for longer term municipal bonds and revenue-only bonds. Consistent with the evidence on municipal bonds, we find that the pricing effects of heat stress on the spreads of corporate bonds are also largely driven by high yield bond issues. In equity markets, we study the conditional expected returns of stocks and find that an increase in corporate exposure to heat stress is associated with a higher expected return in both levered and unlevered terms. These effects of heat stress are robustly significant only after 2013–2015 and are quantitatively substantial ranging from, on a per annum basis, 45 bps (sub-investment grade corporate bonds) to 25 bps (municipal bonds) to 20 bps (equity).

It appears worthwhile in future work to explore the relative importance of heat stress risk relative to other physical risks. Using the Moody's 427 data on physical climate risk exposures at municipal and corporate levels, we do not find much evidence that other dimensions of physical climate risk – estimated damages due to droughts, floods, hurricanes and sea level rise – have systematic asset pricing effects in these three asset classes (see Online Appendix 2.1). This is potentially consistent with these risks being smaller economically and more idiosyncratic (i.e., diversifiable or insurable) compared to heat stress. We recognize, however, that our empirical methodology designed to address the *gradual* geographic variation in heat stress exposures may be less suited for other physical risks whose geographic gradient of variation is higher, allowing for sharper discontinuity-based empirical settings. Clearly, more research is warranted.

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Tables and figures

Table 1: Descriptive statistics for heat stress measures

Panel A presents the summary statistics for heat stress measures in the cross-section of U.S. municipalities. Heat damage (SEAGLAS) is the projected increase in annual heat-related expenditures by the end of the century caused by climate change (RCP 8.5 vs. a counterfactual scenario without climate change) from Hsiang et al. (2017), transformed to dollar damages. Heat score is municipality-level heat stress score estimated by Four Twenty Seven, Inc in February 2020. Δ Proj Hot days is the change in the projected number of hot days (daily maximum temperature > 100°F) per year between 2080-2099 and baseline year 2012 under the RCP8.5 climate scenario, using the average projection of 44 climate change models from Rasmussen et al. (2016). Δ Hot days is the change in the average number of actual hot days between 2001-2010 and 2011-2020. Past Hot days is the average number of heat disaster days in the county over a rolling 3-year window from SHELDUS. Panel B presents the rank correlations for the risk measures. Panel C presents the summary statistics for firm-level sample. To construct a firm-level SEAGLAS measure, we first measure the geographical footprints of U.S. firms using establishment-level data from Dun & Bradstreet Global Archive Files, and them calculate firm-level exposure as the employee-weighted average of the SEAGLAS measure across the counties in which each firm operates.

Panel A: County-level summary statistics

	N	Mean	Std	Min	25%	Median	75%	Max
Heat damage	3143	0.83	0.39	-0.52	0.63	0.87	1.05	1.86
Heat score	3142	61.41	13.00	0.00	53.62	61.57	70.54	100.00
Δ Proj Hot days	3109	38.16	19.31	0.01	23.01	36.96	52.50	108.48
Δ Hot days	3107	0.67	2.79	-8.80	-0.20	0.00	0.40	27.40
Past Hot days	3145	0.36	1.48	0.00	0.00	0.00	0.00	29.37

Panel B: County-level correlations

	Heat damage	Heat score	Δ Proj Hot days	Δ Hot days	Past Hot days
Heat damage	1.00	0.59	0.82	0.35	0.10
Heat score	0.59	1.00	0.41	0.40	0.14
Δ Proj Hot days	0.82	0.41	1.00	0.19	0.07
Δ Hot days	0.35	0.40	0.19	1.00	0.04
Past Hot days	0.10	0.14	0.07	0.04	1.00

Panel C: Firm-level summary statistics

	N	Mean	Std	Min	25%	Median	75%	Max
Heat damage	4649	0.71	0.33	-0.28	0.53	0.71	0.87	1.79
Heat score	618	42.00	7.58	20.09	37.36	41.66	45.11	70.72

Table 2: Summary statistics for asset classes

Table presents the summary statistics for monthly secondary market sample for municipal bonds, corporate bonds, and equities. Spread is the difference between the secondary market yield and maturity-matched benchmark rate. Time to maturity is expressed in years. Credit rating is the average credit rating available from S&P, Moody's, and Fitch, expressed as a numerical value (1=AAA/Aaa, 19=D/C). Turnover is the total trading volume during the past 12 months scaled by total offering amount. Callable and GO are flags that equal to 1 for callable and general obligation bonds, respectively. Energy expenditures are in '$1,000 per capita. High-rating (low rating) subsample includes only bonds with above (below) average credit rating of AA or better (AA- or worse) for municipal bonds, and investment grade (non-investment grade) bonds for corporate bonds. $E_t(R^e_{t+1})$ is annualized 1-month conditional expected return from Martin and Wagner (2019). Size is market capitalization in billions of dollars. Beta is measured using daily return data over the past 12 months on individual stocks and CRSP value-weighted index. Book-to-market, operating profitability, and investment are measured each year in the end of December using most recent annual report available from the past 12-month period, and are then lagged by 6 months. $R_{t-11,t}$ is past 12-month return. Company-level Heat score is estimated by Four Twenty Seven, Inc in December 2019. Sample period is 2006 – 2020.

	N	Mean	Std	Min	25%	Median	75%	Max
Panel A: Municipal bonds								
Spread (bps)	98580	68.92	59.68	0.01	32.14	54.99	83.84	555.83
High rating	69590	52.53	39.22	0.01	27.35	47.05	67.92	555.77
Low rating	28990	108.25	78.92	0.04	54.48	88.31	139.88	555.83
Time to maturity	98580	12.21	7.40	1.00	6.30	11.22	16.93	49.66
Credit rating	98580	3.92	2.45	1.00	2.00	3.00	5.00	19.00
Turnover	98580	0.86	1.22	0.00	0.12	0.31	1.02	5.40
Std(Price)	98580	0.90	0.64	0.00	0.37	0.85	1.31	3.95
Callable	98580	0.82	0.39	0.00	1.00	1.00	1.00	1.00
GO	98580	0.43	0.49	0.00	0.00	0.00	1.00	1.00
Energy expenditures	98580	3.87	0.98	2.38	3.29	3.64	4.27	13.05
County population	98580	0.01	0.00	0.01	0.01	0.01	0.01	0.02
Income per capita	98580	51.38	16.89	17.19	39.09	47.84	59.82	220.42
Unemployment rate	98580	5.84	2.59	1.10	3.94	5.20	7.28	27.70
Debt to revenue	98580	1.57	6.08	0.00	0.00	0.00	0.00	78.00
Past Hot Days	98580	0.88	0.87	0.00	0.08	0.75	1.14	4.16
County fossil score	98580	1.07	0.53	0.00	0.66	0.98	1.37	3.04
Heat score	98580	60.49	11.31	0.00	53.14	58.51	68.62	90.61
Heat damage	98580	0.77	0.36	-0.29	0.57	0.72	0.99	1.86
High rating	69590	0.74	0.36	-0.29	0.56	0.69	0.95	1.86
Low rating	28990	0.85	0.36	-0.23	0.63	0.89	1.05	1.84

	N	Mean	Std	Min	25%	Median	75%	Max
Panel B: Corporate bonds								
Spread (bps)	688561	187.59	175.32	0.00	85.83	137.56	228.85	2675.83
High rating	593710	152.14	130.49	0.00	79.27	122.77	184.97	2675.83
Low rating	94851	409.50	243.94	0.42	265.32	361.42	488.31	2671.73
Time to maturity	688561	10.12	9.88	1.00	3.59	6.59	14.10	99.79
Credit rating	688561	8.19	2.78	1.00	6.00	8.00	10.00	22.00
Turnover	688561	0.69	0.70	0.00	0.22	0.46	0.88	3.75
Std(Price)	688561	1.02	0.97	0.00	0.42	0.77	1.32	9.88
Callable	688561	0.80	0.40	0.00	1.00	1.00	1.00	1.00
Past Hot Days	534555	0.09	0.73	-0.55	-0.31	-0.06	0.24	9.52
Heat score	551937	44.30	7.46	21.72	40.14	42.89	47.58	70.72
Heat damage	534555	0.24	0.69	-2.36	-0.05	0.25	0.52	3.13
High rating	455396	0.21	0.67	-2.15	-0.05	0.24	0.51	3.13
Low rating	79159	0.44	0.80	-2.36	-0.03	0.33	0.82	2.99
Panel C: Equities								
$E_t(R^e_{t+1})$ (bps)	201533	903.19	982.21	0.02	286.39	589.47	1151.87	9973.18
Beta	201498	1.16	0.43	-1.55	0.87	1.11	1.40	4.31
Size ($B)	201533	11.97	42.27	0.02	0.77	2.23	7.84	2255.97
B/M	201322	0.56	0.67	-15.66	0.27	0.46	0.74	21.40
Profitability	200022	0.20	16.03	-860.35	0.15	0.23	0.34	1417.33
Investment	200792	0.13	1.17	-0.93	-0.01	0.06	0.15	233.36
$R_{t-11,t}$	201376	0.15	0.52	-0.99	-0.11	0.10	0.31	27.76
Heat score	67895	43.04	7.38	20.09	38.61	42.25	45.70	70.72
Heat damage	161156	0.06	0.90	-3.15	-0.41	0.09	0.47	2.98

Table 3: Heat stress and muni bond spreads

The table presents estimation results (α_y) for panel regressions of the form

$$Spread_{b,c,t} = \gamma_c + \gamma_t + \sum_{y=2007}^{2020} I_y \left[\alpha_y Risk_c + \theta_y Z_{b,c,t}\right] + \theta X_{b,c,t} + \varepsilon_{b,c,t},$$

where the dependent variable is maturity-matched credit spread in month t of a bond b issued in county c. Control variables include logarithm of the bond's time to maturity, issuer's option to call bond before maturity, flag for general obligation bonds, bond turnover, standard deviation of transaction prices for bond b in month t, energy expenditures per capita, county population, income per capita, unemployment rate, county debt to revenue, number of heat disaster days over the past 3 years, county fossil score of Raimi et al. (2022), and credit-rating fixed effects. Heat score is normalized. Standard errors are two-way clustered by county and month. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Oster (2019) δ is calculated under the assumption that R_{max}=1.

Risk	Heat damage (% GDP)					Heat score				
	coef	se	coef	se	δ	coef	se	coef	se	δ
Risk×I_{2007}	3.15	(5.27)	-5.40	(6.62)	-0.31	2.17	(2.46)	-0.96	(2.32)	-0.17
Risk×I_{2008}	18.63*	(9.74)	12.15	(9.53)	0.46	-0.50	(5.49)	1.82	(3.04)	-0.46
Risk×I_{2009}	39.07**	(16.22)	27.86**	(11.29)	0.58	-1.97	(7.34)	3.27	(3.88)	-0.36
Risk×I_{2010}	15.90	(9.70)	15.74	(10.67)	1.28	-0.71	(5.34)	1.60	(3.66)	-0.40
Risk×I_{2011}	8.84	(9.98)	14.87	(10.23)	-4.34	1.24	(5.30)	0.97	(3.69)	1.27
Risk×I_{2012}	14.27	(9.08)	21.79**	(9.18)	-5.96	4.15	(4.98)	4.62	(3.57)	21.94
Risk×I_{2013}	21.27**	(8.84)	21.85**	(8.58)	2.06	7.76	(4.70)	6.04*	(3.37)	1.32
Risk×I_{2014}	22.42**	(8.95)	21.84**	(8.50)	1.74	9.33**	(4.70)	6.82**	(3.31)	1.09
Risk×I_{2015}	25.71***	(9.13)	26.51***	(8.68)	2.18	10.36**	(4.65)	7.11**	(3.35)	0.91
Risk×I_{2016}	26.83***	(9.28)	27.42***	(8.49)	1.95	10.20**	(4.70)	7.30**	(3.29)	1.01
Risk×I_{2017}	27.85***	(8.99)	27.50***	(8.16)	1.67	9.39**	(4.67)	6.45**	(3.21)	0.92
Risk×I_{2018}	27.52***	(9.15)	28.73***	(8.49)	2.21	9.88**	(4.70)	6.99**	(3.22)	1.00
Risk×I_{2019}	26.18***	(9.50)	26.35***	(8.29)	1.97	9.68**	(4.73)	6.52**	(3.24)	0.88
Risk×I_{2020}	25.91**	(10.37)	25.58***	(8.81)	1.44	9.46*	(4.82)	5.27	(3.30)	0.56
N	98580		98580			98580		98580		
R^2	0.38		0.61			0.38		0.61		
County & Time FE	Y		Y			Y		Y		
Controls	N		Y			N		Y		
Rating x Year FE	N		Y			N		Y		

Table 4: Heat stress and muni bond spreads (matched sample)

The table presents results for a matched sample of municipal bonds, where bonds with high and low exposure to heat stress in the same year-rating category groups are matched based on minimizing the Euclidean distance in standardized coupon rate, time to maturity, county population, income per capita, and unemployment rate. High and low exposure bonds (Treat and Control) are defined as those in the highest and the lowest 20% among all full sample bonds, respectively. The table presents estimation results for panel regressions where the difference in maturity-matched credit spreads between the matched bonds is regressed on year dummies. Heat score is normalized. Standard errors are two-way clustered by treat county and month. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Covariates

Risk	Heat damage (% GDP)		Heat score	
Sample	Treat	Control	Treat	Control
Risk	1.30	0.28	1.25	-1.23
Coupon	3.89	3.88	3.55	3.57
Time to maturity	13.20	12.40	11.27	10.97
County population	0.01	0.01	0.01	0.01
Income per capita	44.26	47.80	43.54	45.42
Unemployment rate	5.71	5.94	5.50	5.80
Debt to revenue	1.35	1.04	1.07	0.96
Rating	4.49	4.49	4.32	4.32

Panel B: Regression coefficients

Risk	Heat damage (% GDP)		Heat score	
I_{2007}	9.27	(9.11)	-8.55	(6.25)
I_{2008}	15.30	(20.57)	-13.96	(16.54)
I_{2009}	18.59	(12.84)	16.11	(12.01)
I_{2010}	12.97	(9.34)	10.56	(8.58)
I_{2011}	1.17	(11.32)	10.45	(10.39)
I_{2012}	22.70^{**}	(8.94)	0.63	(9.79)
I_{2013}	18.13^{**}	(8.71)	12.40	(8.86)
I_{2014}	25.91^{***}	(8.50)	18.55^{**}	(8.19)
I_{2015}	26.83^{***}	(9.18)	19.64^{**}	(7.75)
I_{2016}	29.58^{***}	(9.58)	16.52^{**}	(7.67)
I_{2017}	23.34^{***}	(8.78)	16.52^{**}	(7.39)
I_{2018}	23.82^{***}	(8.54)	14.12^{*}	(7.41)
I_{2019}	23.19^{***}	(8.46)	13.61^{*}	(7.54)
I_{2020}	19.11^{**}	(8.74)	6.43	(9.24)
N	20163		19973	
R^2	0.20		0.17	
County FE	Y		Y	

Table 5: Heat damage and muni bond spreads by subsamples

The table presents estimation results (α_y) for panel regressions of the form

$$Spread_{b,c,t} = \gamma_c + \gamma_t + \sum_{y=2007}^{2020} I_y \left[\alpha_y Risk_c + \theta_y Z_{b,c,t}\right] + \theta X_{b,c,t} + \varepsilon_{b,c,t},$$

where the dependent variable is maturity-matched credit spread in month t of a bond b issued in county c. Control variables include logarithm of the bond's time to maturity, issuer's option to call bond before maturity, flag for general obligation bonds, bond turnover, standard deviation of transaction prices for bond b in month t, energy expenditures per capita, and credit-rating fixed effects. High-rating (low rating) subsample includes only bonds with above (below) average credit rating of AA or better (AA- or worse). Short-term (long-term) subsample includes bonds with less than (more than) 10 years time to maturity. GO and Revenue subsamples only include general obligation and revenue bonds, respectively. Standard errors are two-way clustered by county and month. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Sample	High rating		Low rating		Short-term		Long-term		GO		Revenue	
Heat dmg$\times I_{2007}$	-10.89*	(6.23)	-6.71	(13.28)	-10.03	(11.91)	-7.93	(7.36)	-10.57	(8.84)	4.05	(9.81)
Heat dmg$\times I_{2008}$	-11.74	(10.10)	34.87**	(16.63)	-11.16	(15.14)	22.19*	(11.35)	1.48	(11.29)	26.66**	(12.48)
Heat dmg$\times I_{2009}$	1.53	(12.04)	49.51***	(18.27)	10.38	(14.66)	36.23**	(14.51)	-6.00	(13.52)	45.13***	(14.73)
Heat dmg$\times I_{2010}$	9.05	(12.31)	16.87	(18.30)	-2.16	(14.97)	23.87**	(11.02)	-7.12	(9.97)	25.78*	(14.87)
Heat dmg$\times I_{2011}$	5.61	(10.48)	8.01	(16.80)	1.48	(14.78)	18.87	(11.78)	-24.64**	(9.53)	27.99*	(14.34)
Heat dmg$\times I_{2012}$	16.04	(11.34)	14.93	(17.10)	5.90	(13.62)	28.66***	(10.01)	0.83	(8.72)	25.60*	(13.87)
Heat dmg$\times I_{2013}$	14.61	(10.78)	20.46	(16.33)	7.05	(12.38)	27.14***	(9.47)	-10.69	(8.55)	32.78***	(12.05)
Heat dmg$\times I_{2014}$	12.82	(11.00)	26.05	(16.62)	9.75	(12.64)	25.54***	(9.24)	-13.54	(8.73)	36.30***	(12.23)
Heat dmg$\times I_{2015}$	14.83	(11.39)	37.83**	(16.31)	7.01	(13.12)	35.49***	(9.35)	-6.86	(8.74)	38.13***	(12.33)
Heat dmg$\times I_{2016}$	15.67	(11.50)	40.15**	(16.99)	12.08	(12.94)	33.75***	(9.42)	-2.30	(8.75)	37.39***	(12.55)
Heat dmg$\times I_{2017}$	18.38*	(11.02)	32.47**	(16.18)	11.52	(12.63)	34.97***	(8.99)	-4.46	(8.71)	39.72***	(11.48)
Heat dmg$\times I_{2018}$	19.99*	(11.20)	35.98**	(17.26)	17.74	(12.31)	34.33***	(9.31)	-5.44	(8.54)	44.01***	(12.32)
Heat dmg$\times I_{2019}$	17.76	(10.86)	32.35*	(16.44)	11.24	(12.37)	33.76***	(9.14)	-5.32	(8.66)	37.87***	(11.74)
Heat dmg$\times I_{2020}$	18.26	(11.66)	20.24	(15.16)	14.87	(12.71)	30.62***	(10.04)	-5.22	(9.38)	35.64***	(13.20)
N	69590		28990		42899		55681		42313		53250	
R^2	0.34		0.68		0.66		0.62		0.44		0.64	
County & Time FE	Y											
Controls	Y											
Rating x Year FE	Y											

Table 6: Heat stress and corporate bond spreads

The panel presents estimation results (α_y) for panel regressions of the form

$$Spread_{b,i,t} = \gamma_i + \gamma_t + \sum_{y=2007}^{2020} I_y \left[\alpha_y Risk_i + \theta_y Z_{b,i,t}\right] + \theta X_{b,i,t} + \varepsilon_{b,i,t},$$

where the dependent variable is maturity-matched credit spread in month t of a bond b issued by company i. Control variables include logarithm of the bond's time to maturity, issuer's option to call bond before maturity, bond turnover, standard deviation of transaction prices for bond b in month t, employee-weighted average number of heat disaster days in the counties in which the firm operates over a rolling 3-year window, industry fixed effects (2-digit SIC code), and credit-rating fixed effects. High-rating (low rating) subsample includes only investment grade (non-investment grade) bonds. Last two columns present firm-level estimation results for option-adjusted spread from Morgan Stanley Research (OAS) as y-variable. Heat score is normalized. Standard errors are two-way clustered by company and month. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Heat stress and corporate bond spreads by subsamples

Risk	Heat damage (% GDP)						Heat score					
Sample	Full sample		High rating		Low rating		Full sample		High rating		Low rating	
Risk×I_{2007}	4.87	(3.13)	4.58**	(1.78)	2.24	(7.19)	-3.01	(2.24)	-3.53*	(1.88)	-5.08	(13.99)
Risk×I_{2008}	7.55	(10.50)	17.77*	(9.25)	-23.95	(15.27)	1.33	(9.97)	-0.91	(10.18)	24.62	(26.81)
Risk×I_{2009}	23.06	(14.46)	33.82**	(16.18)	-20.63	(20.73)	-6.98	(20.00)	-2.05	(20.19)	-119.91***	(43.00)
Risk×I_{2010}	11.27*	(5.85)	12.58**	(5.30)	16.70	(13.55)	2.16	(5.50)	1.86	(4.96)	-0.47	(36.52)
Risk×I_{2011}	13.77**	(5.43)	12.07**	(4.78)	37.92***	(14.41)	0.63	(4.93)	-2.47	(4.22)	34.14	(31.78)
Risk×I_{2012}	12.65**	(5.33)	11.20**	(5.05)	44.45***	(14.53)	4.79	(4.58)	0.51	(3.97)	84.62***	(30.00)
Risk×I_{2013}	14.85***	(5.12)	11.41**	(5.38)	44.22***	(14.09)	4.97	(3.77)	0.99	(3.20)	96.59***	(35.52)
Risk×I_{2014}	9.74**	(4.43)	6.19*	(3.66)	42.13***	(14.38)	4.38	(3.62)	0.19	(2.77)	100.60***	(37.65)
Risk×I_{2015}	8.53	(5.43)	4.86	(5.40)	42.51***	(16.10)	7.31	(5.00)	2.47	(4.50)	111.34***	(38.26)
Risk×I_{2016}	12.27**	(5.96)	7.84	(6.25)	51.09***	(15.67)	9.51**	(4.63)	5.89	(4.21)	103.75***	(38.30)
Risk×I_{2017}	9.11**	(4.53)	7.47*	(3.86)	40.71***	(14.81)	6.23	(3.78)	3.33	(3.27)	66.57*	(35.46)
Risk×I_{2018}	8.20*	(4.68)	7.40*	(4.05)	41.59***	(14.52)	1.23	(3.90)	-1.25	(3.67)	67.76*	(36.67)
Risk×I_{2019}	8.14*	(4.53)	7.31*	(4.00)	44.08***	(15.23)	1.42	(3.74)	0.38	(3.32)	72.16*	(37.56)
Risk×I_{2020}	6.04	(5.94)	4.00	(5.73)	49.53***	(18.73)	6.76	(4.34)	7.12*	(4.02)	67.87*	(36.77)
N	529564		451509		78055		397611		368695		28916	
R^2	0.80		0.70		0.82		0.74		0.68		0.84	
Firm & Time FE	Y											
Industry x Year FE	Y											
Controls	Y											
Rating x Year FE	Y											

Panel B: Heat stress and low-rating corporate bond spreads with Oster (2019) δ										
risk	Heat damage (% GDP)					Heat score				
	coef	se	coef	se	δ	coef	se	coef	se	δ
Risk$\times I_{2007}$	-4.67	(9.41)	2.24	(7.19)	-0.10	-3.21	(15.85)	-5.08	(13.99)	-1.80
Risk$\times I_{2008}$	-41.76*	(24.65)	-23.95	(15.27)	0.35	70.99**	(33.63)	24.62	(26.81)	0.15
Risk$\times I_{2009}$	-42.73	(36.83)	-20.63	(20.73)	0.24	-99.97*	(52.82)	-119.91***	(43.00)	4.05
Risk$\times I_{2010}$	25.30	(18.76)	16.70	(13.55)	0.46	13.56	(58.62)	-0.47	(36.52)	-0.01
Risk$\times I_{2011}$	49.57***	(18.52)	37.92***	(14.41)	0.66	51.22	(54.98)	34.14	(31.78)	0.37
Risk$\times I_{2012}$	55.47***	(18.47)	44.45***	(14.53)	0.78	117.21**	(50.36)	84.62***	(30.00)	0.42
Risk$\times I_{2013}$	50.00***	(18.78)	44.22***	(14.09)	1.18	132.10**	(54.23)	96.59***	(35.52)	0.41
Risk$\times I_{2014}$	48.81**	(18.85)	42.13***	(14.38)	1.08	129.65**	(60.48)	100.60***	(37.65)	0.47
Risk$\times I_{2015}$	51.19**	(21.08)	42.51***	(16.10)	0.93	140.39**	(69.53)	111.34***	(38.26)	0.48
Risk$\times I_{2016}$	49.31**	(21.61)	51.09***	(15.67)	4.00	131.44*	(66.71)	103.75***	(38.30)	0.49
Risk$\times I_{2017}$	43.09**	(20.76)	40.71***	(14.81)	2.04	97.39	(62.45)	66.57*	(35.46)	0.34
Risk$\times I_{2018}$	39.61*	(20.80)	41.59***	(14.52)	8.23	97.87	(62.41)	67.76*	(36.67)	0.35
Risk$\times I_{2019}$	41.47*	(21.59)	44.08***	(15.23)	6.30	98.31	(63.20)	72.16*	(37.56)	0.38
Risk$\times I_{2020}$	45.04*	(25.64)	49.53***	(18.73)	34.59	95.30	(65.77)	67.87*	(36.77)	0.38
N	78055		78055			28916		28916		
R^2	0.75		0.82			0.78		0.84		
Firm & Time FE	Y		Y			Y		Y		
Industry x Year FE	Y		Y			Y		Y		
Controls	N		Y			N		Y		
Rating x Year FE	N		Y			N		Y		

Table 7: Heat risk, EDF, and low-rating corporate bond spreads

The panel presents estimation results (α_y, β) for panel regressions of the form

$$Spread_{b,i,t} = \gamma_i + \gamma_t + \sum_{y=2007}^{2020} I_y \left[\alpha_y Risk_i + \beta_y EDF_{i,t} + \theta_y Z_{b,i,t}\right] + \beta EDF_{i,t} + \theta X_{b,i,t} + \varepsilon_{b,i,t},$$

where the dependent variable is maturity-matched credit spread in month t of a bond b issued by company i, and EDF is maturity-matched expected default frequency from Moody's KMV (EDF). Control variables include logarithm of the bond's time to maturity, issuer's option to call bond before maturity, bond turnover, and standard deviation of transaction prices for bond b in month t. Heat score is normalized. Standard errors are two-way clustered by company and month. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

x-var	Heat dmg		EDF		Heat score		EDF	
x-var			1.38	(5.82)			39.54***	(13.36)
x-var$\times I_{2007}$	1.83	(7.40)	1.50	(4.38)	-1.83	(8.65)	-20.10	(14.21)
x-var$\times I_{2008}$	-16.52	(20.86)	38.56***	(7.38)	44.95*	(26.61)	80.49***	(24.73)
x-var$\times I_{2009}$	-24.16	(25.97)	57.77***	(8.71)	-98.51**	(47.17)	10.21	(29.06)
x-var$\times I_{2010}$	21.94	(16.22)	21.56***	(7.13)	-14.09	(55.30)	-9.84	(20.02)
x-var$\times I_{2011}$	44.19***	(16.08)	24.73***	(5.81)	19.96	(51.53)	57.81***	(18.06)
x-var$\times I_{2012}$	50.44***	(15.54)	27.87***	(5.45)	79.73*	(45.49)	50.06***	(18.86)
x-var$\times I_{2013}$	42.84***	(14.64)	14.32***	(4.95)	89.95*	(48.37)	17.86	(22.46)
x-var$\times I_{2014}$	39.73***	(15.11)	14.73***	(5.56)	87.81*	(50.83)	-23.03	(20.48)
x-var$\times I_{2015}$	40.64**	(16.94)	32.00***	(7.41)	88.52	(55.62)	-1.20	(28.30)
x-var$\times I_{2016}$	40.54**	(17.38)	35.03***	(7.06)	93.27*	(53.00)	27.39*	(16.47)
x-var$\times I_{2017}$	35.78**	(16.37)	7.30	(5.94)	64.15	(51.80)	-10.90	(14.87)
x-var$\times I_{2018}$	32.74**	(16.28)	5.56	(5.95)	65.65	(52.54)	-26.04*	(15.05)
x-var$\times I_{2019}$	43.30**	(16.69)	11.78**	(5.70)	68.81	(53.43)	-21.26	(14.09)
x-var$\times I_{2020}$	29.75	(22.02)	12.82*	(6.56)	69.92	(54.09)	3.47	(14.61)
N	77205				28899			
R^2	0.82				0.83			
Firm & Time FE	Y							
Industry x Year FE	Y							
Controls	Y							
EDF x Year	Y							

Table 8: Heat stress and conditional expected returns on equity

The table presents estimation results (α_y) for panel regressions of the form

$$E_t(R_{i,t+1}) = \gamma_i + \gamma_t + \sum_{y=2007}^{2020} I_y \alpha_y Risk_i + \theta X_{i,t} + \varepsilon_{i,t}$$

where the dependent variable is the annualized expected excess return in month t of company i using the methodology of Martin and Wagner (2019). Control variables include market beta, size, book-to-market, profitability, investment, and past 12-month returns. $E_t(R_{t+1})$ and $E_t(R_{t+1\to t+12})$ use 1-month and 1-year expected return as y-variable, respectively. Last two columns unlevers expected equity returns by multiplying it with $(1 - L_{i,t})$, where L_t is financial leverage, defined as the sum of long-term debt and debt in current liabilities, divided by total assets. Heat score is normalized. Standard errors are two-way clustered by company and month. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Heat damage (% GDP)

y-variable	$E_t(R_{t+1})$		$E_t(R_{t+1\to t+12})$		$E_t(R_{t+1})(1-L_t)$		$E_t(R_{t+1\to t+12})(1-L_t)$	
Risk$\times I_{2007}$	21.31***	(7.49)	27.14***	(8.90)	9.82	(6.26)	18.80**	(7.63)
Risk$\times I_{2008}$	13.90	(16.38)	13.16	(16.56)	3.20	(14.55)	3.52	(14.31)
Risk$\times I_{2009}$	32.60**	(14.12)	27.09*	(15.89)	13.47	(11.69)	11.19	(13.07)
Risk$\times I_{2010}$	15.45	(9.45)	14.28	(10.39)	4.04	(8.06)	6.86	(8.58)
Risk$\times I_{2011}$	17.23*	(9.74)	7.18	(12.16)	3.28	(8.70)	-1.02	(10.10)
Risk$\times I_{2012}$	11.63	(8.36)	6.90	(9.27)	0.02	(7.61)	-2.06	(8.14)
Risk$\times I_{2013}$	8.53	(8.90)	2.74	(9.25)	0.18	(9.10)	-2.46	(8.83)
Risk$\times I_{2014}$	11.33	(8.78)	8.64	(8.69)	3.54	(8.27)	3.03	(7.85)
Risk$\times I_{2015}$	16.88*	(9.51)	16.25	(10.09)	8.28	(8.76)	10.71	(8.68)
Risk$\times I_{2016}$	19.84**	(9.36)	18.46*	(9.61)	16.10*	(8.21)	15.35*	(8.02)
Risk$\times I_{2017}$	13.60	(9.00)	17.39*	(9.65)	13.81*	(7.57)	16.84**	(7.71)
Risk$\times I_{2018}$	23.86**	(9.24)	22.74**	(10.08)	20.08**	(7.79)	20.01**	(8.00)
Risk$\times I_{2019}$	23.49**	(10.14)	26.29**	(10.64)	18.69**	(8.36)	20.75**	(8.52)
Risk$\times I_{2020}$	28.26**	(11.46)	26.32**	(11.74)	13.20	(10.26)	17.99*	(9.85)
N	67838		67806		67738		67704	
R^2	0.88		0.83		0.86		0.83	
Firm & Time FE	Y		Y		Y		Y	
Industry x Year FE	Y		Y		Y		Y	
Controls	Y		Y		Y		Y	

Panel B: Heat score								
y-variable	$E_t(R_{t+1})$		$E_t(R_{t+1\to t+12})$		$E_t(R_{t+1})(1-L_t)$		$E_t(R_{t+1\to t+12})(1-L_t)$	
Risk×I_{2007}	3.89	(6.21)	3.00	(5.96)	-1.58	(4.98)	0.03	(4.62)
Risk×I_{2008}	-2.13	(17.86)	7.15	(12.91)	-14.88	(16.45)	-2.80	(11.02)
Risk×I_{2009}	18.05	(14.27)	21.24	(13.57)	-1.74	(11.47)	4.13	(10.45)
Risk×I_{2010}	10.60	(8.43)	10.57	(7.77)	-0.88	(6.93)	0.22	(6.74)
Risk×I_{2011}	9.22	(8.53)	15.08**	(7.42)	0.66	(7.65)	7.66	(6.10)
Risk×I_{2012}	6.58	(7.68)	8.94	(6.83)	5.68	(6.37)	7.89	(5.77)
Risk×I_{2013}	3.43	(7.12)	4.50	(6.87)	3.23	(5.97)	4.63	(5.68)
Risk×I_{2014}	5.18	(8.09)	5.53	(7.34)	2.82	(6.82)	3.61	(6.10)
Risk×I_{2015}	15.24*	(7.86)	14.53**	(7.06)	11.45*	(6.54)	11.84**	(5.85)
Risk×I_{2016}	27.33***	(8.16)	22.18***	(6.88)	25.09***	(7.14)	21.78***	(6.03)
Risk×I_{2017}	18.45**	(8.62)	17.75**	(7.54)	20.79***	(7.53)	21.45***	(6.52)
Risk×I_{2018}	12.95	(8.74)	17.49**	(7.91)	13.59**	(6.60)	18.25***	(6.34)
Risk×I_{2019}	22.55**	(9.21)	25.11***	(8.94)	22.75***	(7.94)	24.57***	(7.62)
Risk×I_{2020}	31.49**	(13.38)	29.02***	(10.69)	12.05	(10.83)	18.91**	(7.96)
N	50037		50007		49982		49952	
R^2	0.87		0.84		0.84		0.82	
Firm & Time FE	Y		Y		Y		Y	
Industry x Year FE	Y		Y		Y		Y	
Controls	Y		Y		Y		Y	

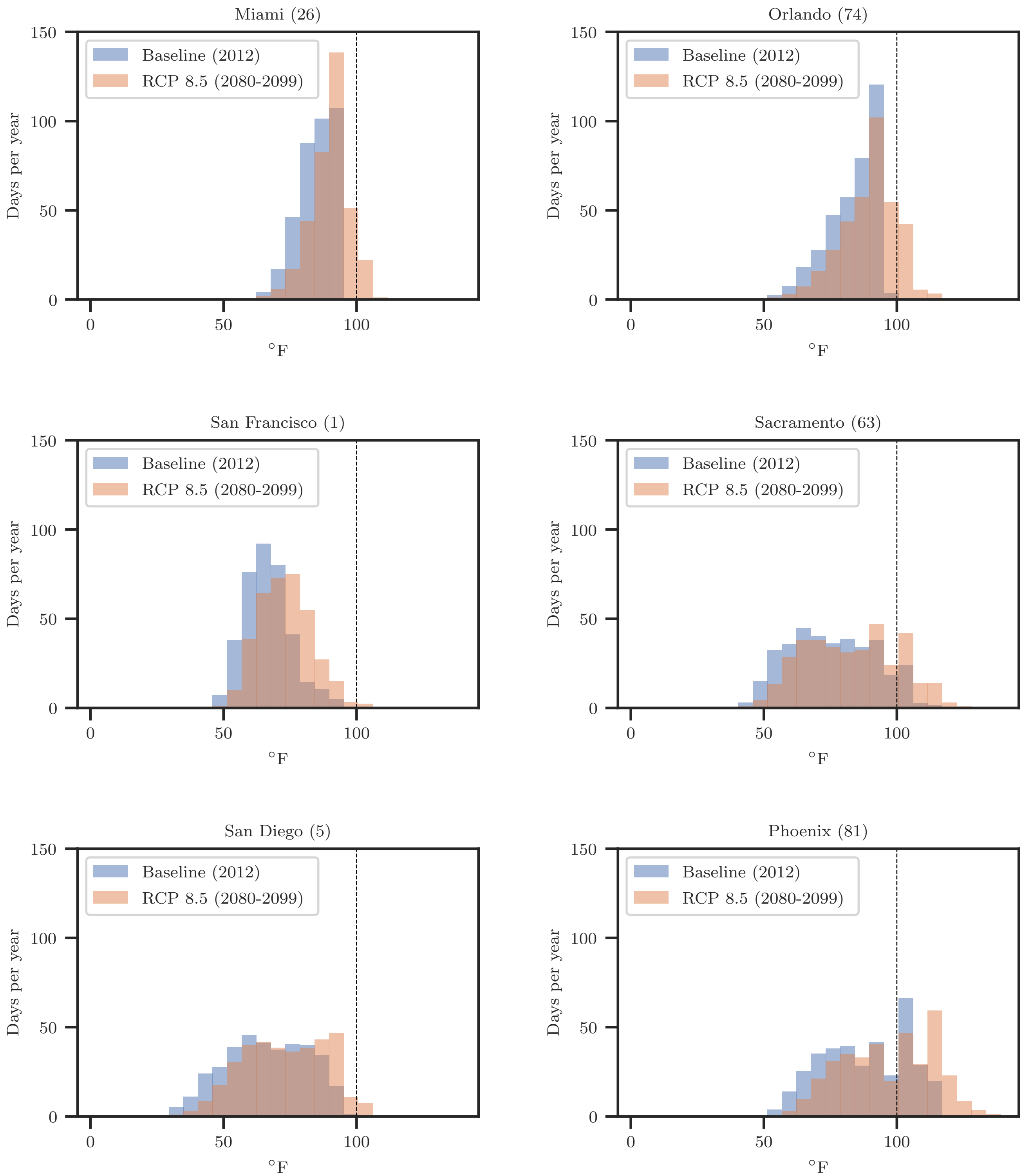
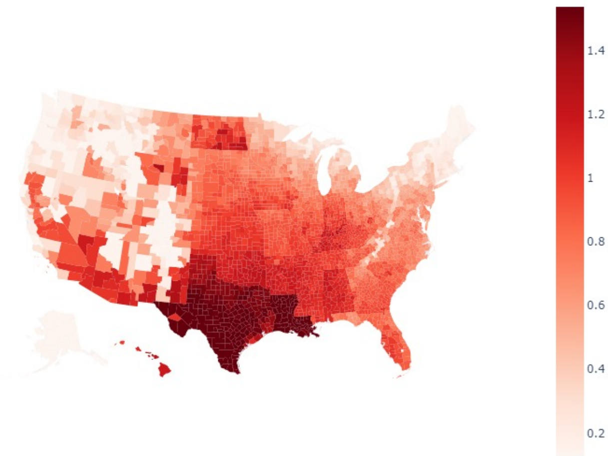
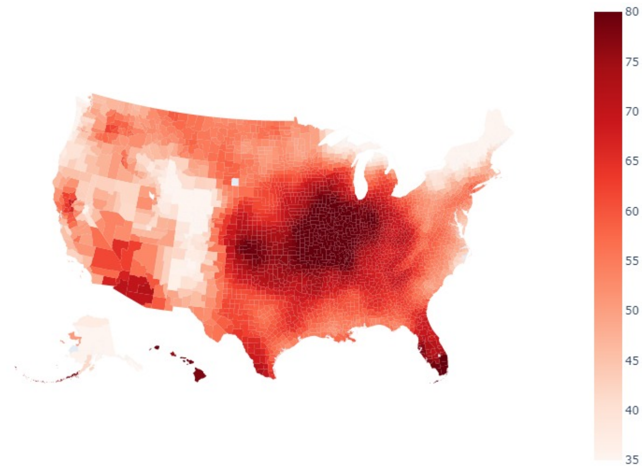


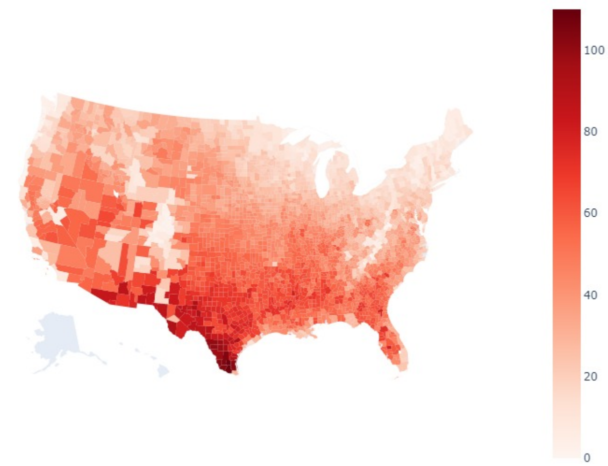
Figure 2: **Annual temperature distributions under Baseline and RCP 8.5 scenarios.** Counties' percentile ranks in terms of an increase in the number of +100°F days are shown in parentheses.



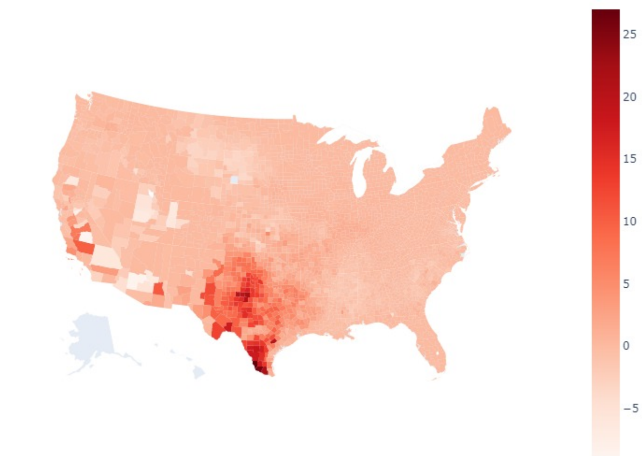
(a) Heat damage (% GDP)



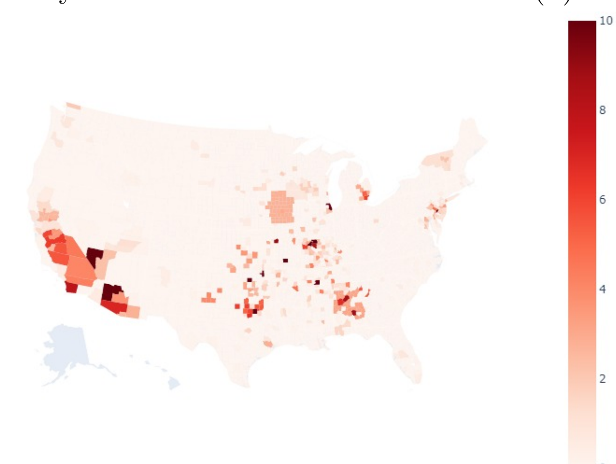
(b) Heat score



(c) Δ Proj Hot days



(d) Δ Hot days



(e) Past Hot days

Figure 3: **Physical risk exposure by county.** The figure shows geographical distribution of measures of physical risk exposure.

Online appendix to
"Is physical climate risk priced? Evidence from regional variation in exposure to heat stress"

Appendix 1: Matching municipal bonds to counties

Since our climate exposure variables are available at municipality-level (FIPS code), we need to determine which geographical area a given bond is associated with. Ideally, we would like to do this for each bond regardless of the identity of the issuer (e.g. municipality, city, school district, utility). Unfortunately, there is little such information directly available for the universe of municipal bonds.

To overcome this issue, we proceed as follows. For each municipal bond, we observe the state of the issuance and the issuer name as reported in the initial CUSIP filing. The name can be something as straightforward as "ANCHORAGE ALASKA" or something more complicated such as "ABAG FIN AUTH FOR NONPROFIT CORPS CALIF REV" (Association of Bay Area Governments Finance Authority for Nonprofit Corporations). We download the list of states, counties and county-equivalents, county subdivisions, incorporated and census designated places from U.S. Board on Geographic Names website (with their associated FIPS codes). We refer to these name data as "Census names". Our goal is to use string matching to find (preferably one) Census name that is associated with each CUSIP name.

Before matching, we take the following steps to preprocess and clean the names:

1. Clean Census names of various prefixes and suffixes (e.g. "Municipality of Anchorage" → "Anchorage"). However, there are six cases in which the same name is associated with two counties (e.g. Baltimore City and Baltimore County are both counties in Maryland[25]). In these cases, we attach 'CNTY' suffix with the county and manually check that the algorithm is able to assign bonds to the correct entity.

[25] Other such cases are St. Louis (MO), Fairfax (VA), Franklin (VA), Richmond (VA), and Roanoke (VA).

2. Remove special characters (e.g. dots, commas, dashes) and replace Non-English characters with their English counterparts (e.g. "San José" → San Jose) in both CUSIP and Census names

3. Remove duplicate place names. If subdivision and place have same names, use subdivision because it is generally larger entity subsuming place and more likely to issue bond. If incorporated place and Census Designated Place (CDP) have same names, use incorporated place.

4. Expand the common abbreviations in CUSIP names (e.g. "HBR" → "Harbor"). Exception: we always abbreviate "Saint" with "ST" in both CUSIP and Census names.

Next, we remove any white spaces from Census names (e.g. "ST LOUIS" → "STLOUIS"), and within each state, we find Census names that are substrings of CUSIP names with arbitrary white spaces allowed in the middle (e.g. "ST LOUIS MO REV" matches to "STLOUIS").

While this approach works well for majority of bonds, it creates some false positives especially when county or place name is some general word (e.g. county named PARK or LAKE, or a town called YORK in the state of New York). For such general words[26] we impose some additional requirements for a match:

1. CUSIP name string starts with Census name and the next word is state name or abbreviation (e.g. LAKE MINN is matched to LAKE (county) but PRIOR LAKE MINN ECONOMIC DEV is not)

2. In CUSIP name, the next word after a county Census name is a county keyword

[26] We identified the following set of general words if Census names: 'POINT', 'FORT', 'PARK', 'VALLEY', 'RIVER', 'CENTER', 'CORNER', 'HARBOR', 'ISLAND', 'UNION', 'LAKE', 'GREEN', 'NORTH', 'EAST', 'SOUTH', 'WEST', 'NORTHEAST', 'NORTHWEST', 'SOUTHEAST', 'SOUTHWEST', 'NORTHERN', 'EASTERN', 'WESTERN', 'BAY', 'CITY', 'GROVE', 'FALLS', 'HILL', 'HILLS', 'HALL', 'ROCK', 'STONE', 'UPPER', 'LOWER', 'MIDDLE', 'CANYON', 'IRON', 'COVE', 'TEMPLE', 'PLAINS', 'PLAIN', 'OAK', 'GATEWAY', 'GAS', 'PRIOR', 'BLUE', 'HOLIDAY', 'COMMERCE', 'JUSTICE', 'COLLEGE', 'UNIVERSITY', 'GAP', 'PROGRESS', 'ARP'. Furthermore, we handle York, NY, and Dakota, SD, manually withing those states to avoid a large number of false positives.

('COUNTY, 'CNTY', 'PARISH') (e.g. SOUTH LAKE CNTY HOSP DIST FLA gets matched to LAKE (county))

3. CUSIP name contains plural county keyword when matched to a county Census name (e.g. LAKE & SANDERS CNTYS MONT HIGH gets matched to LAKE (county))

4. In CUSIP name, the next word after a place Census name is a place keyword ('CITY', 'TWP', 'CHARTER TWP', 'NEW YORK N Y') (e.g. SPRING LAKE TWP MINN gets matched to LAKE (place))

This matching process allows us to find at least one matching state, county or place name for [X] of municipal bonds. However, in many cases we get several matches which oftentimes is undesirable (e.g. issuer named ANCHORAGE ALASKA gets matched both to the municipality of Anchorage and to the state of Alaska. Issuer named NEW YORK N Y gets matched to place (city), county and state of New York). To get rid of these multiple matches, we proceed as follows.

1. If CUSIP name is matched with multiple counties or places where one Census name is a substring of other, keep the longer (e.g. NORTHSALTLAKE and SALTLAKE (places)).

2. If CUSIP name is matched with state name and county or place name, keep the latter (e.g. Alaska match is deleted for ANCHORAGE ALASKA).

   - Exception: in some cases, there is identical state name and county/place name within the same state.[27] In these cases, keep state match unless the CUSIP name contains county or place keywords.

3. If CUSIP name is matched to both county and places, remove any matches that are substrings of others (e.g. PALO ALTO CNTY IOWA HOSP REV is matched to both PALOALTO (county) and PALO (place). Remove latter.)

[27] ARIZONA, ARKANSAS, DISTRICTOFCOLUMBIA, GUAM, HAWAII, IDAHO, IOWA, NEWYORK, OHIO, OKLAHOMA, UTAH.

4. If CUSIP name gets matched to exactly same county and place names, use counties unless there are place keywords that indicate the opposite (in most cases, this choice does not matter because the place with the same name as the county is within that county.)

5. If CUSIP name is still matched to both counties and places, remove places if county-words are present and placewords are not present in CUSIP name (and vice versa).

6. If CUSIP name is still matched to both counties and places, remove place matches. This residual rule is needed in less than 1% of matches.

After this step, most of the bonds are associated with only one geographical location, but some of them are still matched with multiple counties or places (e.g. LAKE & SANDERS CNTYS MONT HIGH is matched with both Lake and Sanders counties). In the vast majority of such cases, this is due to the bond being in fact issued jointly by multiple entities. Furthermore, we get some more multiple matches when we convert place FIPS codes to county FIPS codes because some places are geographically located in multiple counties (e.g. New York City gets matched to five counties associated with the five boroughs of the city).

After having converted everything to County FIPS level, we match our risk exposure data with the bonds and take average score in the cases when bond is matched with multiple county FIPS codes.

Appendix 2: Additional results

Table A1: Heat stress and muni bond spreads (other exposures)

The table shows the coefficients of selected control variables used in the regressions shown in Table 3. The variables include the number of heat disaster days over the past 3 years, energy expenditures per capita, and county fossil score of Raimi et al. (2022). Standard errors are two-way clustered by county and month. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: Heat damage (% GDP)							
	Heat dmg		Past temperature		Energy cost		Transition risk	
x-var$\times I_{2007}$	-5.40	(6.62)	-5.06**	(1.96)	0.32	(0.40)	3.38	(3.20)
x-var$\times I_{2008}$	12.15	(9.53)	-2.24	(3.10)	-0.24	(0.46)	0.90	(3.28)
x-var$\times I_{2009}$	27.86**	(11.29)	-1.99	(4.27)	-0.67*	(0.34)	-1.78	(5.25)
x-var$\times I_{2010}$	15.74	(10.67)	-6.50	(4.07)	-0.78***	(0.20)	1.49	(3.58)
x-var$\times I_{2011}$	14.87	(10.23)	-5.43	(4.69)	-0.72***	(0.21)	-2.13	(2.80)
x-var$\times I_{2012}$	21.79**	(9.18)	-6.70*	(3.95)	-0.34**	(0.14)	-3.97	(3.28)
x-var$\times I_{2013}$	21.85**	(8.58)	-5.15	(3.64)	-0.04	(0.09)	-3.63*	(2.14)
x-var$\times I_{2014}$	21.84**	(8.50)	-6.32*	(3.46)	-0.14	(0.09)	-1.61	(2.17)
x-var$\times I_{2015}$	26.51***	(8.68)	-7.36**	(3.66)	-0.15	(0.17)	-1.52	(3.53)
x-var$\times I_{2016}$	27.42***	(8.49)	-7.52**	(3.55)	-0.23*	(0.14)	-2.29	(4.38)
x-var$\times I_{2017}$	27.50***	(8.16)	-8.04**	(3.40)	-0.32***	(0.11)	-2.15	(3.27)
x-var$\times I_{2018}$	28.73***	(8.49)	-8.59**	(3.44)	-0.31***	(0.10)	-1.82	(2.95)
x-var$\times I_{2019}$	26.35***	(8.29)	-9.21***	(3.46)	-0.20**	(0.09)	-1.35	(3.12)
x-var$\times I_{2020}$	25.58***	(8.81)	-8.78**	(3.41)	-0.30***	(0.11)	-3.80	(4.47)
N	98580							
R^2	0.61							
	Panel B: Heat score							
x-var	Heat score		Past temperature		Energy cost		Transition risk	
x-var$\times I_{2007}$	-0.96	(2.32)	-4.02**	(1.85)	0.15	(0.44)	-1.54	(2.94)
x-var$\times I_{2008}$	1.82	(3.04)	-0.34	(3.27)	-0.22	(0.45)	-0.31	(2.75)
x-var$\times I_{2009}$	3.27	(3.88)	0.46	(4.32)	-0.51	(0.35)	-0.24	(4.38)
x-var$\times I_{2010}$	1.60	(3.66)	-4.35	(4.22)	-0.62***	(0.21)	0.32	(3.11)
x-var$\times I_{2011}$	0.97	(3.69)	-3.49	(4.64)	-0.67***	(0.21)	-3.23	(2.74)
x-var$\times I_{2012}$	4.62	(3.57)	-4.13	(3.98)	-0.34**	(0.13)	-3.83	(3.33)
x-var$\times I_{2013}$	6.04*	(3.37)	-2.39	(3.60)	-0.07	(0.09)	-3.55	(2.15)
x-var$\times I_{2014}$	6.82**	(3.31)	-3.48	(3.43)	-0.19**	(0.08)	-1.48	(2.16)
x-var$\times I_{2015}$	7.11**	(3.35)	-4.30	(3.72)	-0.19	(0.16)	-0.23	(3.56)
x-var$\times I_{2016}$	7.30**	(3.29)	-4.48	(3.63)	-0.25**	(0.12)	-0.62	(4.26)
x-var$\times I_{2017}$	6.45**	(3.21)	-5.15	(3.50)	-0.31***	(0.12)	-0.58	(3.35)
x-var$\times I_{2018}$	6.99**	(3.22)	-5.61	(3.52)	-0.30***	(0.10)	-0.28	(2.89)
x-var$\times I_{2019}$	6.52**	(3.24)	-6.37*	(3.51)	-0.20**	(0.09)	-0.25	(3.16)
x-var$\times I_{2020}$	5.27	(3.30)	-6.00*	(3.51)	-0.28**	(0.11)	-2.77	(4.36)
N	98580							
R^2	0.61							
County & Time FE	Y							
Controls	Y							
Rating x Year FE	Y							

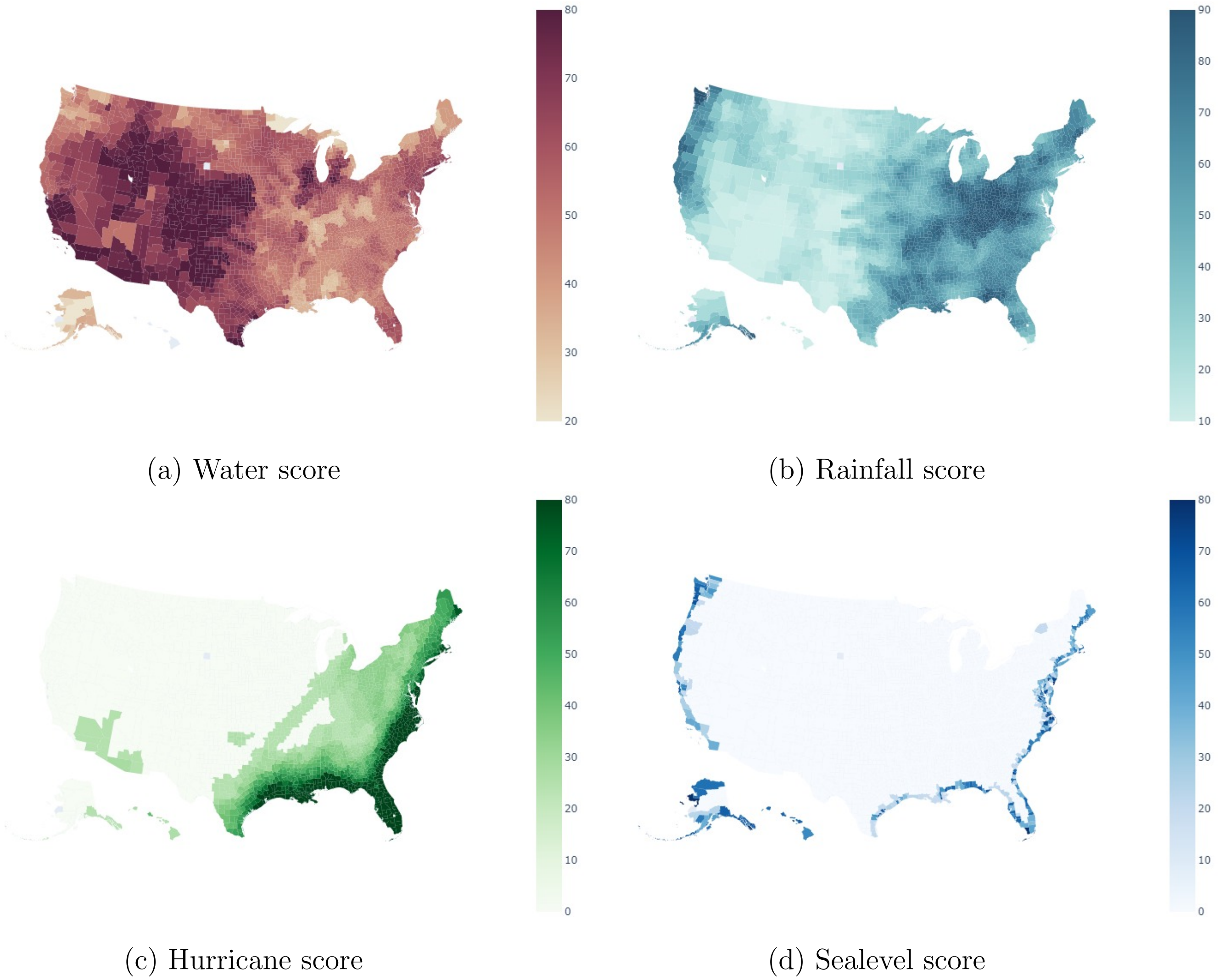
Appendix 2.1: Other physical climate risks

In addition to heat stress, the two physical exposure datasets provides us with exposure measures for various other physical climate risks, viz., water/drought risk (which is partly related to heat stress), flooding risk, hurricane risk, and sea level rise risk. In this section, we will repeat our analyses for these other exposure measures in order to assess their importance relative to heat stress. We do this with a major caveat though: because we measure risk exposure at county level, any within-county variation in risk exposure introduces noise in our x variable (physical climate risk exposure) and biases results towards zero. While this is likely to be a minor problem for our main variable of interest (heat stress), it is likely to be important for some other risk categories with large exposure gradients. This is especially true for sea level exposure (see Panel (d) in Figure A1).

More generally, if exposure for heat stress was more precisely measured than exposure to other climate hazards, any differences in pricing results could simply reflect these differences in measurement errors. However, we find this unlikely to be the case. Catastrophe risk models for hurricanes, for example, have received a significant amount of development since 1980s and are significantly more sophisticated than any heat stress models that we are aware of. Furthermore, the geographical concentration of hurricane risk is higher in the first place. Indeed, the rank correlation between hurricane measures from Hsiang et al. (2017) and 427 is 0.79 compared to 0.59 for heat stress, suggesting that there is indeed less disagreement about the measurement of the former than the latter.

With this caveat in mind, Table A2 provides the results for municipal bonds, corporate bonds, and equities, respectively. For municipal bonds, we fail to detect any impact on hazards other than heat stress, although for drought (water) risk the estimates have qualitatively somewhat similar pattern. Qualitatively, our result for sea level risk also seems consistent with Painter (2020) who finds that yields for exposed counties were elevated compared to other counties in 2007 compared to 2006, but also with Goldsmith-Pinkham et al. (2023) who find that such effects disappeared afterwards. The fact that our between-county comparison fails to detect any impact is also consistent with Goldsmith-Pinkham et al. (2023) who stress the importance of within-county comparison to uncover the impact of sea level risk on spreads.

For corporate bonds and equities, the conclusion is by and large similar: we fail to detect risk premia on physical climate risks other than heat stress. An interesting exception is flood risk for equities which shows a pattern similar to heat stress, although overall less conclusively so. However, this pattern is not present for corporate bonds. Overall, we conclude that a consistent pricing of physical climate risks between municipal bonds, corporate bonds and equities appears evident only for heat stress and not so for the other four physical climate risks in SEAGLAS and 427 measures.



(a) Water score

(b) Rainfall score

(c) Hurricane score

(d) Sealevel score

Figure A1: **Other physical risk exposures by county.** The figure shows geographical distribution of measures of physical risk exposure.

Table A2: All risk scores

The table presents estimation results for municipal bonds (from Table 3), non-investment grade corporate bonds (From Table 6 Panel A), and equities (From Table 8), where all available physical climate risk measures are included as explanatory variables. Risk scores are normalized.

Panel A: Municipal Bonds										
Risk	Heat score		Water score		Rainfall score		Hurricane score		Sealevel score	
Risk$\times 1_{2007}$	-0.78	(2.41)	-2.70	(2.83)	-1.75	(2.61)	-0.23	(2.02)	2.36^{*}	(1.32)
Risk$\times 1_{2008}$	2.14	(3.48)	-2.89	(3.54)	-3.05	(3.21)	7.36^{***}	(2.49)	0.06	(1.91)
Risk$\times 1_{2009}$	2.16	(3.63)	7.45^{*}	(4.43)	7.23^{*}	(4.33)	6.20^{*}	(3.51)	-1.42	(2.25)
Risk$\times 1_{2010}$	1.72	(3.65)	3.77	(4.23)	-0.73	(3.80)	2.45	(3.06)	-5.58^{**}	(2.40)
Risk$\times 1_{2011}$	-0.23	(3.77)	4.41	(4.15)	5.58	(4.41)	-0.81	(3.14)	-3.54	(2.70)
Risk$\times 1_{2012}$	4.89	(3.57)	3.68	(4.02)	1.48	(3.75)	-0.29	(3.29)	-1.69	(2.50)
Risk$\times 1_{2013}$	5.94^{*}	(3.40)	2.54	(3.81)	1.50	(3.69)	0.64	(2.98)	-2.12	(2.19)
Risk$\times 1_{2014}$	6.60^{*}	(3.39)	2.40	(3.91)	2.56	(3.70)	-0.25	(3.00)	-1.22	(2.27)
Risk$\times 1_{2015}$	7.23^{**}	(3.43)	4.27	(3.93)	2.46	(3.65)	0.78	(3.04)	-0.74	(2.38)
Risk$\times 1_{2016}$	7.71^{**}	(3.36)	3.77	(3.81)	0.39	(3.51)	2.31	(2.95)	-1.69	(2.31)
Risk$\times 1_{2017}$	6.92^{**}	(3.29)	4.36	(3.77)	0.66	(3.48)	2.10	(2.92)	-1.94	(2.21)
Risk$\times 1_{2018}$	7.26^{**}	(3.33)	3.13	(3.80)	0.20	(3.55)	3.41	(3.00)	-2.31	(2.23)
Risk$\times 1_{2019}$	6.81^{**}	(3.34)	2.88	(3.80)	0.35	(3.55)	1.27	(2.99)	-1.81	(2.24)
Risk$\times 1_{2020}$	5.89^{*}	(3.44)	3.02	(3.89)	-0.98	(3.67)	1.65	(3.11)	-0.67	(2.32)
N	98442									
R^2	0.61									
County & Time FE	Y									
Controls	Y									
Rating x Year FE	Y									

Panel B: Corporate Bonds										
Risk	Heat score		Water score		Flood score		Hurricane score		Sealevel score	
Risk×I_{2007}	-54.09*	(31.01)	0.50	(7.91)	60.69***	(21.53)	39.07*	(21.02)	-33.98	(29.63)
Risk×I_{2008}	39.34	(69.38)	3.07	(27.06)	-11.79	(49.52)	-30.71	(35.98)	31.66	(48.97)
Risk×I_{2009}	-151.86***	(46.38)	-0.91	(25.74)	16.31	(36.51)	85.61	(63.06)	-30.61	(41.95)
Risk×I_{2010}	-21.59	(38.52)	55.01***	(15.00)	11.13	(19.99)	7.32	(27.49)	-47.11	(30.50)
Risk×I_{2011}	21.09	(40.63)	56.49***	(20.20)	12.48	(19.86)	-5.82	(42.37)	-58.12*	(34.01)
Risk×I_{2012}	62.84	(41.07)	41.31	(25.11)	-6.18	(21.69)	29.10	(44.24)	-81.86**	(31.82)
Risk×I_{2013}	79.21*	(42.40)	63.66**	(24.60)	21.97	(21.97)	10.65	(42.98)	-81.18**	(32.24)
Risk×I_{2014}	89.88**	(41.42)	44.60**	(21.22)	12.86	(23.23)	-10.71	(41.27)	-77.32**	(29.59)
Risk×I_{2015}	104.25***	(39.27)	21.36	(26.69)	35.05	(26.17)	-38.08	(39.30)	-81.73***	(30.19)
Risk×I_{2016}	97.02**	(39.50)	30.10	(27.96)	20.75	(24.18)	-31.67	(41.02)	-76.56**	(32.25)
Risk×I_{2017}	88.26**	(35.39)	-1.77	(28.53)	16.16	(25.33)	-52.07	(43.00)	-70.53**	(35.22)
Risk×I_{2018}	106.90***	(37.56)	-20.86	(28.41)	26.85	(26.43)	-23.43	(41.22)	-93.48***	(31.55)
Risk×I_{2019}	105.45***	(36.88)	-9.14	(26.99)	36.67	(25.93)	-19.74	(38.32)	-97.60***	(31.52)
Risk×I_{2020}	103.42**	(41.97)	-3.06	(32.45)	31.63	(28.51)	-3.15	(40.87)	-89.10***	(32.83)
N	28916									
R^2	0.85									
Firm & Time FE	Y									
Industry x Year FE	Y									
Controls	Y									
Rating x Year FE	Y									

Panel C: Equities

Risk	Heat score		Water score		Flood score		Hurricane score		Sealevel score	
Risk$\times I_{2007}$	11.73*	(6.83)	-21.10***	(6.94)	0.24	(5.06)	-4.86	(4.45)	10.69**	(5.18)
Risk$\times I_{2008}$	20.23	(20.43)	-28.86	(17.60)	13.39	(16.83)	-26.21*	(15.04)	33.88*	(20.23)
Risk$\times I_{2009}$	30.79*	(16.81)	-14.21	(14.06)	12.91	(12.11)	-16.79	(11.85)	19.94	(16.73)
Risk$\times I_{2010}$	10.46	(9.02)	-14.79*	(8.28)	1.99	(6.43)	-6.04	(6.50)	-7.86	(7.54)
Risk$\times I_{2011}$	8.33	(9.27)	-16.92*	(8.85)	10.51	(8.56)	-4.80	(6.91)	-13.04*	(7.88)
Risk$\times I_{2012}$	7.18	(8.75)	-9.59	(7.40)	4.26	(6.66)	-8.06	(5.93)	-5.94	(6.71)
Risk$\times I_{2013}$	7.29	(8.26)	-7.02	(7.16)	0.48	(6.41)	-8.18	(5.95)	3.95	(6.19)
Risk$\times I_{2014}$	5.31	(9.06)	-5.29	(7.49)	9.11	(6.99)	-1.24	(5.98)	-5.74	(6.43)
Risk$\times I_{2015}$	14.28	(9.04)	-4.03	(7.69)	10.42	(7.23)	-3.17	(6.57)	-6.99	(7.26)
Risk$\times I_{2016}$	23.95**	(9.66)	-2.33	(7.94)	12.54	(7.61)	0.82	(6.99)	-11.99	(7.63)
Risk$\times I_{2017}$	15.29	(9.91)	1.97	(8.04)	3.43	(7.66)	7.07	(6.30)	-4.90	(7.24)
Risk$\times I_{2018}$	12.54	(10.11)	-8.33	(8.20)	13.14*	(7.36)	-5.39	(6.11)	-8.40	(6.95)
Risk$\times I_{2019}$	17.62	(11.01)	-4.08	(9.07)	13.75	(9.05)	-0.65	(7.92)	-16.65**	(8.22)
Risk$\times I_{2020}$	24.90*	(13.73)	3.19	(11.19)	15.83	(11.50)	-0.50	(10.08)	-16.91	(10.44)
N	50037									
R^2	0.87									
Firm & Time FE	Y									
Industry x Year FE	Y									
Controls	Y									