Is Physical Climate Risk Priced? Evidence from Regional Variation in Exposure to Heat Stress*

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Abstract

We exploit regional variations in exposure to heat stress to study if physical climate risk is priced in municipal and corporate bonds as well as in equity markets. We find consistent evidence across asset classes that local exposure to heat stress is associated with higher yield spreads for bonds, especially for lowe-quality and longer-maturity bonds, as well as higher conditional expected returns for stocks. These results are observed robustly starting in 2013–15, and are consistent with macroeconomic models where climate change has a direct negative impact on aggregate consumption.

Keywords: Climate finance, Physical climate risk, Heat waves, Municipal bonds, Asset pricing

JEL Classification: G12, Q54

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1 Introduction

Climate change is expected to cause direct damages to society by amplifying many natural hazards and understanding how climate-related risks affect the cost of capital is crucial for making decisions about investment in mitigation.[1] While concerns about global warming initiated much of the research on climate risk, implications of heat stress exposure for asset prices are not well understood. Among the candidate climate change risks, heat stress exposure stands out quantitatively as the most significant contributor to economic damages. Importantly, estimates by Hsiang et al. (2017) suggest that by the end of the century, annual damages 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,[2] while damages associated with increased hurricane activity are estimated to be an order of magnitude smaller at around 0.1% of GDP each year. Similarly, estimates in Hallegatte et al. (2013) suggest that damages related to sea-level rise are relatively modest at around 0.1% of GDP.

A recent paper by 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.[3]

[1] The risk appears to be manifesting itself along several physical dimensions: a) heat stress, which refers to increase in the frequency of heat waves over time; b) droughts, which is partly but not entirely related to heat stress; c) floods, which can cause extensive damages in a relatively short period of time; d) hurricanes, which has increased in intensity and frequency in different parts of the world; and, e) sea level rise, affecting predominantly coastal areas.

[2] 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).

[3] 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.

However, economic exposure to heat stress extends much beyond wildfire risk, even when the risk manifests only in a gradual 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.[4] 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.[5]

To reiterate, while heat stress is the primary 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 from (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, 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 physical climate risk 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 large U.S. stocks. 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 classes in the form of increased credit spreads and risk premia. In addition, we characterize the important channels through which heat stress affects asset prices, namely through increased energy expenditures and lowered labor productivity.

The main empirical challenge when estimating the effect of physical climate risk exposure

[4] 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.

[5] See, for example, *California debates naming heatwaves to underscore deadly risk of extreme heat*, The Guardian, 1 March 2022.

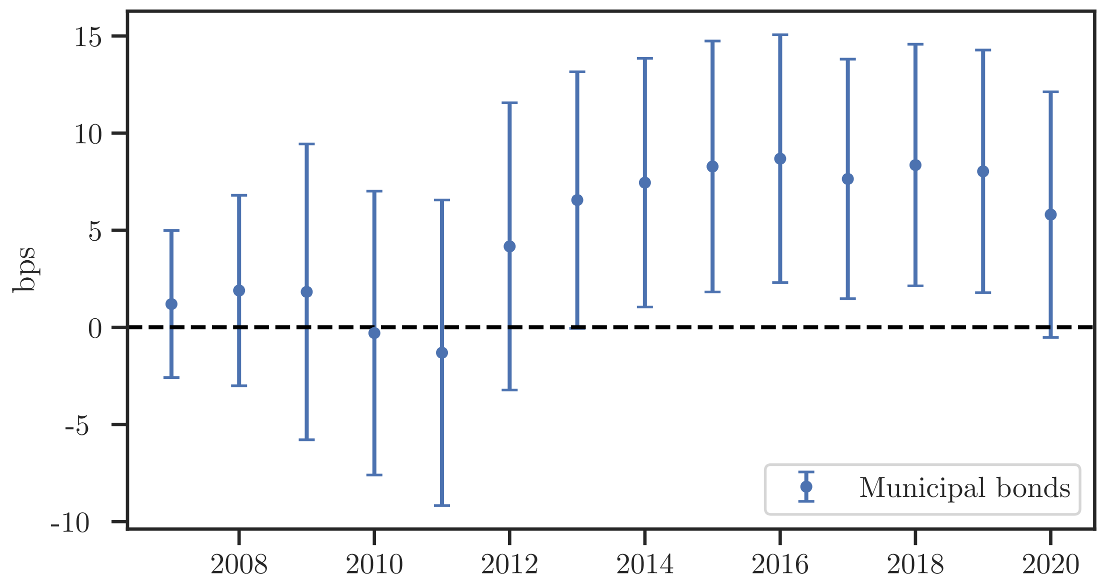
on asset prices is that they may be correlated with some other important sources of cash flow risk (see e.g. Goldsmith-Pinkham et al., 2022). We tackle this problem directly with flexible credit rating x year fixed effects to control for issuer-level heterogeneity in overall creditworthiness, essentially 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, very 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 any biases and omissions in the credit rating process. To 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.[6] 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.

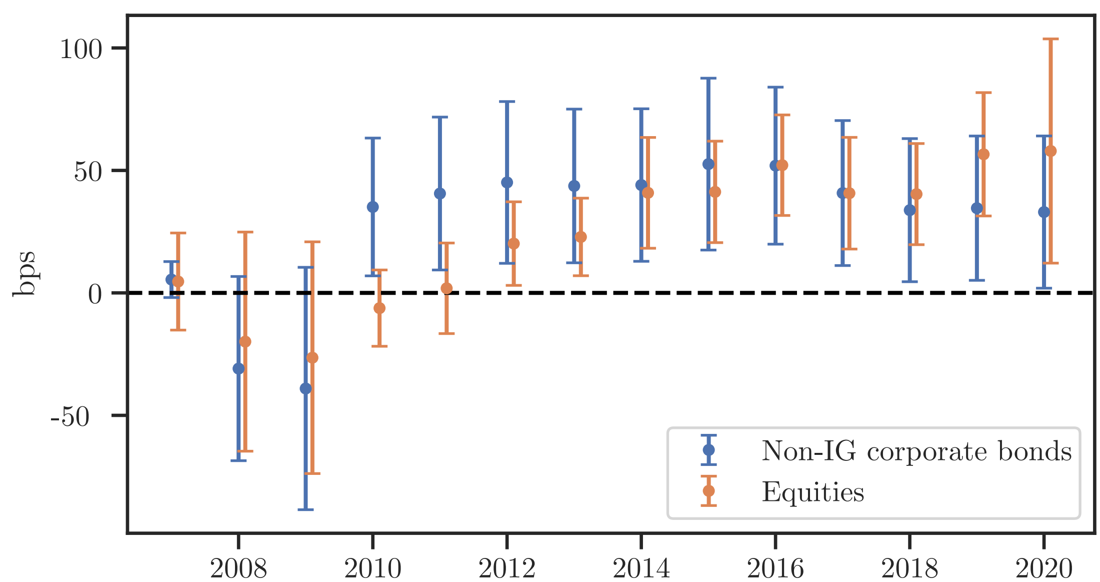
1.1 Summary of main results

Our main findings, summarized for the 427 measure in Figure 1, are as follows. For municipal bonds, we find that a one standard deviation increase in heat stress exposure is associated

[6] See e.g. Florackis et al. (2023) and Kacperczyk and Peydró (2022) for similar approaches in closely related contexts.



(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 7 (Column 3), and Table 8 (Column 2) for full results.

with yield spreads that are higher by around 5 basis points per annum (bps).[7] Similar results for SEAGLAS measure – that allows us to assess the absolute impact of heat related damages to yield spreads – suggest that exposure to heat stress related annual damages that equal 1% of GDP are associated with around 15 bps higher credit spreads compared to a municipality not exposed to such losses. 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., 2022, 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.

As mentioned earlier, extreme heat can cause damages to the local economy through several different channels. During hot weather, energy demand increases substantially mainly due to increased need for cooling (which today constitutes around 10% of all electricity consumption in the U.S.). Also, energy supply is adversely impacted due to the decreased efficiency of electricity production when ambient temperatures are high. Furthermore, labor productivity is adversely affected by hot weather, especially in high-risk industries such as construction and mining where workers are directly exposed to outside temperatures.[8] Fi-

[7]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.

[8]As a recent example of direct impact of heat stress on outdoor labor productivity, Oregon's Occupational Safety and Health Administration (OHSA) 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).

nally, extreme temperatures have negative impacts on human health increasing healthcare costs and mortality. After establishing our main results, we take a closer look at these individual channels. This analysis reveals that the effect of heat stress on credit spreads is mainly related to an expected increase in energy expenditures and decrease in labor productivity in high-risk industries, with little evidence for projected decrease in labor productivity in low-risk industries (e.g. service industry) and excess mortality. One interpretation of these findings is that adaptation for different channels of temperature exposure is important in mapping heat stress to economic costs.[9]

We find qualitatively similar results in corporate bond spreads. Among S&P 500 companies, a one standard deviation increase in exposure to heat stress is associated with yield spreads that are higher by around 40 bps for sub-investment grade corporate bonds, with little effect for investment grade bond spreads.[10] Unlike municipal bonds whose claims are often subordinated to the pension fund claims on municipalities,[11] corporate bonds are senior to equity holders and thus are better protected, especially if the issuer is of investment grade.[12] This intuition suggests that the heat stress exposure impact in corporate claims are likely borne more by high-yield bond investors (and equity holders) who have a lower position in the priority structure.

Importantly, to confirm that heat stress exposure indeed affects cash flows of companies, we show that it directly affects their expected default frequency (EDF), and consistent with our other results, the effect is stronger for longer-horizon EDF. Moody's KMV's EDF measure uses a structural model based distance-to-default and maps it into a statistical probability of default using historical default experience data. When we examine the impact of heat stress exposure on credit spreads controlling for EDF (which includes both climate damages and

[9]The importance of endogenous adaptation to heat stress in measuring welfare losses has been emphasized in Heal and Park (2013) and Heutel et al. (2021).

[10]Our results are robust to examining "option-adjusted" spreads (OAS) that account for embedded options such as callability or putability of bonds.

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

[12]Moreover, municipalities, counties and utilities have fixed locations, whereas a corporate entity can shift its physical assets to mitigate climate-related risks.

non-climate cash flow risk), we find that (i) the effect of firm-level EDF on spreads is in line with a reasonable assumption on loss given default; and, (ii) the residual effect of heat stress on spreads remains positive but is dampened and is not as robust over time statistically. Together, these results can be interpreted as the risk premium on climate damages being of a similar order of magnitude – or possibly higher – as that on the non-climate cash flow risk in firm-level EDFs.

The distinction between expected climate damages and the premium on this risk is crucial not only from an asset-pricing perspective, but also because different macroeconomic models of climate change make different predictions on the sign of this premium (see, e.g., Giglio et al., 2021). This distinction can also have a large impact on private incentives to mitigate climate change risk such as climate abatement investment decisions, and hence on optimal climate policy. 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 a one standard deviation increase in heat stress exposure is associated on average with around 45 bps increase in annual expected returns for S&P 500 companies.

We recognize that our earlier results on the impact of heat stress on credit spreads and EDFs 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. 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 lower at 30 bps increase per annum. Highly consistent with our earlier findings in municipal bond markets, this difference first emerged around 2013 with little evidence during earlier years. This result suggests that the equity market premium on physical climate risk is positive.

2 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. 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.

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 (2020, 2021) 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-intense firms have more 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. (2022) 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. (2022) also find such a relation but with 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 shows 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. Analyzing corporate bonds in particular allows us to separate out the cash-flow and expected-return effects of heat stress exposures, both of which we identify to be at work in asset prices.

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.

3 Data

3.1 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 supply (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")[13] scenarios using 44 existing climate models and model surrogates from Rasmussen et al. (2016) at a weather station level. 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 these 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. 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. Comparing Orlando and Miami, for example, we see that neither city

[13]RCP 8.5 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.

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 s, 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[14] were paid in 2019 and convert it to per-capita measure. 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 our measure. Similarly, the measure does not capture any heat-related damages to agriculture or human health. Furthermore, the measure does not account for the compounding effect of humidity on energy expenditures and labor productivity.[15] These limitations likely cause us

[14] 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)

[15] We note though that the magnitude of these compounding impacts are considered by some researchers

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 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 aggregates 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,

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.

and sea level rise. For most of the paper we will focus on heat score, but employ these other scores in the final analysis of the paper (Section 5) when evaluating the asset-pricing impact of heat stress relative to these other physical climate risks.

In addition to being proprietary, the main limitation of the second measure compared to the first one is its relative nature: we can observe 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 are available for companies in addition to municipalities.

One limitation common to both our 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).

Figure 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.[16]

Figure 3 panels (f) to (i) plot the exposure scores for other physical climate risks which we will discuss in Section 5. A higher score in a particular risk category indicates a higher exposure. Unsurprisingly, scores associated with coastal risks (hurricanes, sea level rise, and flood to some extent) are more skewed than the ones associated with other risks like heat and water stress. This is because exposure to coastal risk is concentrated on relatively small geographical areas (coasts) while the other risks also affects regions that are land bound.

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, with increase in energy expenditures having the largest contribution to the aggregate measure (0.58%). Damages related to the decrease in labor productivity in high and low risk

[16]Note that for heat damage, state borders are sometimes clearly visible in the graph. This is mainly due to the fact that we use state-level data on wages and energy consumption to convert Hsiang et al. (2017) intensive measures to dollar damages. Our results are not sensitive to this transformation, as we obtain similar results in our asset pricing tests if we use Δ Proj Hot days as our x-variable that is not subject to these transformations.

industries both also contribute substantially to the aggregate measure (0.14% and 0.11%, respectively).[17] 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 based on the so-called "wet bulb" temperature measure of Behrer et al. (2021). The first one – Hot days – is the average number of days per year between 2011 and 2020 when the maximum wet bulb temperature in the county was above 100°F. In recent history, such heat waves were relatively rare and distribution heavily skewed: the median county experienced only 0.4 hot days per year, with the maximum being 116.8 in Yuma County, AZ. This current level is in a stark contrast to the projected increase in heat wave frequency, with the frequency increasing from the current level of 0.4 days per year by 38.16 days per year for the average municipality.

The second historical 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 second component is conceptually more closely related to our heat stress measures than the first one. 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.[18] Table 3 panels (d) and (e) plot the distributions of Hot days and Δ Hot days across the U.S.

Table 1 Panel B shows the rank correlations of our risk measures. Both wet-bulb tempera-

[17]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.

[18]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.

ture measures are positively rank-correlated with SEAGLAS and 427 risk measures (0.35 and 0.68 for Heat damage, and 0.40 and 0.47 for 427 Heat score), suggesting that our measures are indeed related to cross-sectional variation in temperature levels and trends. That said, the relatively modest correlations between historical temperature measures and measures based on future 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.

Next, we describe the municipality and company level data sets that we merge with our exposure data.

3.2 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. 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. (2022), 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.

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.

3.3 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.[19] We measure bond turnover 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.

3.4 Equities

As discussed in the introduction, an important objective of the paper is to try to distinguish the effects of heat stress on expected returns (risk premia) from effects on expected losses. For this, we turn to the cross-section of equities.[20] 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,

[19] 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 risk-free rates in both markets instead.

[20] Effects of heat stress exposure on a firm's expected cash flows do, of course, affect stock prices. But they should not affect the firm's expected return other than through the risk premium channel. Equity expected returns can also be affected by expected losses via the amplifying effect of leverage, which we will investigate below.

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.[21]

To overcome this problem, we follow Martin and Wagner (2019) to 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 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:

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

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), $\text{call}_{i,t}(K)$ and $\text{put}_{i,t}(K)$ 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

[21] 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 whole sample period.

market regressions is

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

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. (2021). 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 $SVIX^2_m$ 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.

4 Empirical approach and results

4.1 Municipal bonds

4.1.1 Identification strategy

As seen in Figure 3, the cross-sectional variation in our risk measures is driven by geographic locations of the municipalities. As a consequence, a challenge we face is that local economic conditions also vary across the country, affecting creditworthiness of bond issuers and hence the credit spreads of their bonds. As stressed by Goldsmith-Pinkham et al. (2022), 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. (2022) 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, exploiting such spatial discontinuities is unfortunately not feasible. Temperature by its very nature changes only gradually across locations, which is apparent by comparing Panels (b) and (h) of Figure 3: 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.[22]

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

[22]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.

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 for 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.[23]

Despite the prominent role of physical climate risks in the revised framework, these risks have only resulted in a very 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[24] 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.

[23] See Moody's Investors Service (2020) and Fitch Ratings (2021) for similar white papers from the other agencies.

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

To assess more systematically how climate risks have been accounted for in municipal bond markets, we parsed through the vast majority of municipal bond prospectuses since 2010, and counted how many of them mention "climate change" somewhere in the document, using such mention as a proxy for climate risks being explicitly accounted for.The resulting time series, shown in Figure 4, is very much consistent with our previous narrative: until very recently, only a small number ($\approx 3\%$) of prospectuses contained at least a single mention of climate change. While this has been changing quite rapidly in recent years, the fraction of such prospectuses is still only 16% during the first half of 2020.

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.[25]

4.1.2 Results

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

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

[25] 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. Further, this coefficient stability serves to bound the potential impact of hypothetical omitted variables on our results. See the Oster (2019) tests that we report in Appendix A.

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 from EIA, 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 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., 2022). 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 17.10 bps higher credit spread compared to a case with no climate risk exposure.[26] Based on our second (427) measure, one standard deviation increase in heat stress exposure increases spreads by 7.76 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

[26]Some caution should be exerted when interpreting the magnitude though: our bottom-up measure for heat stress exposure does not capture all channels through which extreme heat causes damage to the economy, resulting in per-unit-of GDP effects being overestimated. This caveat is discussed more in Section 4.1.3.

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 2.7 and 1.8 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 around twice 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. The full results of this analysis are shown in Appendix Table A2.

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.[27] 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.[28] 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:

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

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

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

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 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.

4.1.3 Mechanism

After establishing our main result that exposure to extreme heat affects municipal bond spreads, we take a closer look at each individual channel through which extreme heat causes damages to the economy. As discussed in Section 3.1, our aggregate damage measure consists of three components: damages related to climate change-induced increase in energy expenditures, decrease in labor productivity in industries where workers are directly exposed to outside temperatures ("high-risk labor"), and decrease in labor productivity in other industries ("low-risk labor"). We can use these separate components on the right side of our regressions.

Results are shown in Table 6. For both energy expenditures and high-risk labor, the patterns are similar to the ones obtained with the aggregate measures: higher exposure to both risk measures is associated with higher credit spreads, but only during the second half of the sample.[29] Interestingly, the third component of heat damages, viz. low-risk labor, does

[29]Note the large magnitudes of the coefficients compared to the main estimates in Table 3. For example, our 2019 estimate for high-risk labor suggests that a county that is expected to suffer damages that equal to 1% of GDP as a result of decrease in labor productivity in high risk-industries must pay 1.23% higher spread for its debt. This reflects the fact that such estimate assumes that excess heat only causes damages through

not produce results consistent with the earlier patterns. While many coefficients for low-risk labor seem to be positive and highly significant, this seems to be related to abnormal (noisy) baseline year of 2006. For example, our coefficient estimates for 2011 and 2019 are not materially different, suggesting spreads have not become more sensitive to this exposure over time. The results for the matching approach (presented in the Online Appendix Table A3) confirm this interpretation: while the patterns for other risk measures look similar to the main estimates, there is little significance for low-risk labor overall.

Finally, the table shows that the qualitative nature of our pricing results is robust to using as measure of heat stress risk the raw measure for projected change in heat wave frequency (Δ Proj Hot days), which is the main climate input variable in SEAGLAS. The point estimate for 2019, for example, suggests that spreads increase by 0.29 bps for each additional hot day per year. Overall, the result is consistent with our main estimates, suggesting that the main source of variation driving our pricing result is indeed related to the variation in expected temperature increases, instead of variation in some economic variables that SEAGLAS takes as inputs to transform projected temperature increases into projected damages.

4.2 Corporate bonds

Next, we turn our attention from municipal bonds to corporate bonds. Here, the main limitation we face is that our risk measure from Hsiang et al. (2017) is not available for corporations.[30] Instead, we proceed with 427 risk scores only. Given that the two measures were highly correlated and yielded consistent results in the municipal bond sample, we are less concerned about losing the ability to cross-validate results with the two different measures. However, by focusing only on risk scores we lose ability to estimate absolute magnitudes of how climate damages affect bond spreads. Therefore, we must focus on relative comparisons only when interpreting the estimated coefficients.

high-risk labor productivity channel, which significantly underestimates the total damages.

[30]Mapping the measure of Hsiang et al. (2017) to a company-level is not feasible due to its geographical focus on the U.S. To be implementable, one would need exposure data (and facility location data) for U.S. corporations globally.

We continue to use credit ratings to control for the impact of unobserved non-climate factors that affect firms' creditworthiness. More specifically, we run 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, 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 Panel A of Table 7. 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 around 2013. However, the statistical and economic significance of these results is weak in the overall sample. The results are, however, much stronger when focusing on non-investment grade bonds. For these securities, a one standard deviation in an issuer's heat stress is associated with an increased credit spread of 33 bps to 53 bps, going back to 2010.[31] In contrast, the effect of heat stress exposure on investment grade bond spreads is virtually non-existent.

Next, we present some additional results for corporate bonds as robustness checks.[32] First, we obtained data on option-adjusted spreads (OAS) from Morgan Stanley Research, ICE for S&P 500 companies (ICE, 2019). This data set is distinct from our Mergent FISD-TRACE data set and allows us to observe weighted average OAS at firm-level. We append these data by adding control variables for liquidity using company-level averages from Mergent FISD-

[31] Again, average Oster (2019)'s δ for our coefficient estimates is 1.9, implying that in order for an unobserved covariate to explain our results, it would need to be around twice as influential for credit spreads as the factors captured by credit ratings and other control variables. See Appendix Table A2 for full results.

[32] Due to much smaller cross-section of bonds (especially in the non-investment grade category where the results are concentrated in), a matching approach similar to the one presented in Table 4 for municipal bonds is unfortunately not a feasible robustness check.

TRACE. Since OAS explicitly account for optionalities built into specific corporate bonds issues, these data allow us to confirm that our results are not driven by any confounding effects related to embedded options such as callability and also controlling for time-varying level differences in spreads between bonds with and without such optionality. Indeed, this is what we find in the last columns of Table 7 Panel A; the effect of heat stress on corporate bond OAS is found to arise starting in 2013 and only for junk-rated bonds, even though the statistical significance is less uniform than in the main analysis.

Second, 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.[33] Therefore, we replace corporate bond spread by the EDF as our dependent variable in order to tease out the impact of heat stress on the cash flow component of credit risk. More specifically, we estimate

$$EDF_{i,t} = \gamma_i + \gamma_t + \sum_{y=2007}^{2020} I_y \left[\alpha_y Risk_i + \theta_y \gamma_{c,t}\right] + \theta\gamma_{c,t} + \varepsilon_{b,i,t}, \tag{8}$$

where $\gamma_{c,t}$ are credit rating dummies. Table 7 Panel B presents the results. We find that higher heat stress exposure is associated with higher EDF during most years in our sample, indicating that more exposed bonds are indeed more risky from a cash flow perspective; this appears to be true for junk-rated bonds with a rising magnitude from 2007 to 2020, and for investment grade bonds with a lower but also rising magnitude from 2015 to 2020. Furthermore, we present results for EDF of non-IG bonds at different horizons (1, 2, 5, and 10 years). Results become stronger with longer horizon, consistent with our municipal bond results in Table 5.

Given the evidence that heat stress is related to a decrease in cash flows through increased

[33]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.

default frequencies, the next natural question to ask is if this exposure is associated with a separate (climate) risk premium or not. Note that our previous results on credit spreads do not allow us to disentangle the impact of a decrease in expected cash flows from a risk premium (roughly speaking, a credit spread is the expected loss amplified by a risk premium). 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.

Since Table 7 Panel B suggests that EDF captures cash flow risk to bonds from climate as well as non-climate sources, in Table 7 Panel C we regress credit spreads on heat stress exposure controlling for EDF:

$$Spread_{b,i,t} = \gamma_i + \gamma_t + \sum_{y=2007}^{2020} I_y \left[\alpha_y Risk_i + \beta_y EDF_{i,t} + \theta_y Z_{b,i,t}\right] + \beta EDF_{i,t} + \theta X_{b,i,t} + \varepsilon_{b,i,t}. \quad (9)$$

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. 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.

While the coefficients on heat stress are on average positive after 2010, they are statistically weak, albeit with some statistical significance between 2012 and 2017 (and also with economic significance then for high-yield bonds). We interpret this result as the risk premium in corporate bonds on heat-stress related climate damages being of a similar order of magnitude – or possibly higher – as that on the non-climate cash-flow risk. Given that corporate bonds 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 30-40% and rises for sub-IG bonds especially during years of stress such as 2008-09 (global financial crisis), 2012 (European sovereign debt crisis), 2016 (Chinese devaluation), and 2020 (COVID).

4.3 Equities

To make further progress in disentangling the price of climate risk from its negative impact on expected cash flows, we will 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 run a regression similar to the one in the case of municipal bonds:

$$E_t(R_{i,t+1}) = \gamma_i + \gamma_t + \sum_{y=2007}^{2020} I_y \alpha_y Risk_i + \theta X_{i,t} + \varepsilon_{i,t}, \tag{10}$$

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. 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.

Results are shown in 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 2012. On average, the estimates suggest that a one standard deviation increase in heat stress exposure increases expected returns by around 45 bps, which corresponds to an approximately 10% increase compared to the unconditional mean. Interestingly, this magnitude is very similar to the one we estimated for municipal bonds but smaller than that for junk-rated corporate bonds.

The coefficient pattern is seen to be similar across alternative methodologies and samples.

The second specification restricts to firms that have data for the entire period, i.e., whether or not they are in the S&P 500 index. The third specification imposes the restriction that the firms' risk-neutral beta is between 0.0 and 2.0 as a validity check on a key assumption of the Martin and Wagner (2019) measures.[34] The fourth specification uses longer horizon options to estimate a year-ahead expected return and uses that as the dependent variable.[35]

Finally, the last specification follows Doshi et al. (2019) in unlevering equity expected returns to get an estimate of firm expected returns. Since we have shown that heat stress is associated positively with expected default frequency and hence with market leverage, 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 30 bps, especially since 2013, supporting our overall interpretation.

4.4 Discussion

Before we consider other physical climate risks, a few observations are in order.

4.4.1 Negative heat stress coefficient prior to 2012

In several of our specifications, we find negative coefficients on the heat stress variable during some or all of the years 2008 to 2012, e.g., investment-grade (IG) corporate debt and the equity tests.

Given that we find negative coefficients even in equity tests where the dependent variable is specifically designed to reflect expected returns, the finding of negative coefficients could

[34] The approximation in Martin and Wagner (2019) is more accurate when β^* is close to one, see Section I of Online Appendix to Martin and Wagner, 2019 for more detailed description.

[35] 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.

be related to risk premia. As discussed in Giglio et al. (2021), there are indeed theoretical models that can deliver either sign for a climate (temperature) risk premium. In particular, the argument in Nordhaus (2014) for a negative risk premium is that investors worry that avoiding global warming would require engineering a huge recession, with major contractions in output and consumption, so that marginal utility might actually be higher in a cooler future than in a hotter one.

Hence, one possibility is that these types of beliefs could have been predominant in 2008-2009 when the global financial crisis was unfolding; the economy was in a deep recession; the Copenhagen climate change conference of December 2009 raised the possibility that governments would take climate action in the near-term; and if they did so at an especially vulnerable time, this could have been bearish for global growth. In such times, stocks that would benefit from less heat risk could – at the time – have been a good hedge against this outcome. The change in coefficient signs to being positive since 2012 may thus be a reflection that the underlying macroeconomic scenario turned substantially benign since then, and risk premia adhered thereafter to the more intuitive channel that climate (heat) stress directly reduces aggregate output, as in Bansal et al. (2021).

There are also other possible explanations. Energy prices fell substantially starting in mid-2008, which could have reduced the energy expenditure bill for counties most exposed to heat stress, improving their credit quality in a relative sense compared to less exposed states. While data on energy expenditures are not available at firm level, imputing such expenditures (using geographic establishment-level data for firms and annual state-level per capita energy expenditures) does not substantially affect our results for corporate bonds and equities. On balance, we conclude that it is an interesting finding that risk premia on heat stress appear to be more uniformly positive only since 2012, but clearly more needs to be done as longer time-series become available to understand their conditional variation.

4.4.2 Positive heat stress coefficient since 2013

The equity market results suggest that at least a significant component of the increased bond credit spread effects since 2013 are likely to be the result of an increasing heat stress risk premium. The increasing risk premium could be due to an increase in the risk itself (as perceived by investors) or by 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 an increased awareness of the risk or an increased appreciation of its systematic nature.

The period since 2013, also, of course, 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).

4.4.3 Climate change risk or energy risk

Given that our measures suggest that climate change damages mainly manifest themselves as an increase in energy expenditures, it is reasonable to ask if our heat stress measures simply capture cross-sectional differences in exposure to energy price fluctuations, that could be a priced source of risk even in the absence of climate change. In this section, we study such alternative hypothesis.

To measure and control for municipal bond issuers' exposure to energy price fluctuations, we obtain per capital energy expenditure data from U.S. Energy Information Administration (EIA). These data is available at state-year level ending in 2020. Between 2006 and 2020, average energy expenditures per capita is \$4,301, ranging from \$2,380 to \$13,047. Most of the variation in energy expenditures is cross-sectional in nature, with state fixed effects explaining 78% of the variation during the sample period. Per capita energy expenditures are positively but relatively modestly rank correlated with average heat stress measures, with these correlations being 0.27 and 0.16 for Heat damage and Heat score measures.

Such modest correlations are perhaps explained by the fact that energy expenditures tend to be high both in hot and cold climates with a high number of cooling degree days and heating degree days, respectively. Indeed, the five states with the highest energy expenditures—Alaska, Wyoming, Louisiana, North Dakota, and Texas—consists of some of the coldest and hottest states in the country. Out heat stress measures, on the other hand, suggest that energy expenditures in many cold regions are in fact likely to decrease as a result of climate change due to decrease in heating degree days, while currently hot regions will experience even more cooling degree days increasing energy expenditures even further. This observation likely explains why controlling for current level of energy expenditures have little impact on our pricing results.

Measuring companies' energy expenditures is significantly less straightforward than for states. We first obtain company-level annual energy consumption data (in Gigajoules) from Refinitiv ESG database. In 2019, we had data available for 335 S&P 500 companies, with availability deteriorating quite fast when going back in time, with 237 companies available in 2015.

We measure firm energy intensity as annual energy consumption per \$1M revenue. Similar to municipalities, energy intensity is very stable over time: in firm-year panel from 2015 to 2019, firm fixed effects have and R-squared of 0.95. Given the high degree of stability and limited data availability and in the time series, we will use 2019 energy intensity measures as a proxy for historical energy intensity. Given this, our firm-year level energy expenditure measure is a product of firm's 2019 energy intensity times year t U.S. average energy price from EIA. For firms without energy consumption data, we use average energy intensity of firms in the same Fama-French 17 industry portfolio.

Tables 9 and 10 repeat our main corporate bond and equity analyses while controlling for firm-year-level energy expenditures. Due to data availability, the sample period ends in 2019. Overall, the results look very similar to our main estimates, suggesting that differential exposure to energy price fluctuations is unlikely to explain our results.

5 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 physical climate risks – heat, drought, flooding, hurricanes and sea level rise – on financial asset prices, focusing attention specifically on the pricing of heat stress risk.

Using two complementary data sets, we document empirical evidence for a significant effect of heat stress on three distinct asset classes. First, we show that heat stress is priced in both municipal credit spreads 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; for issuers of these bonds, we document a direct effect of heat stress on their expected default frequency, consistent with expected climate damages affecting cash flows on bonds. In equity markets, we study the conditional expected returns of stocks in the S&P 500 index 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 15 bps (municipal bonds) to 45 bps (equity).

Our consistent finding across all three asset classes of an increasing trend in the cost of capital associated with heat stress may be attributable to a perceived increase in the risk itself, or to increasing investor awareness of the risk and of its systematic nature. The paper also briefly explores the channels through which heat stress affects the pricing of asset classes studied in the paper and finds that the energy expenditures and decrease in labor productivity in industries more exposed to heat stress are the primary channels.

Finally, 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 (see Appendix B) 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. This is potentially consistent with these risks being smaller economically and more idiosyncratic (i.e., diversifiable and/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. 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. Energy damage is the projected increase in annual energy 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 using 2019 data on state-level energy expenditures. High-risk labor is the projected decrease in labor productivity in high-risk industries from Hsiang et al. (2017), transformed to dollar damages using 2019 data on state-level employee compensation for high-risk industries. 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). Low-risk labor is an equivalent measure for all the other industries. All three measures are scaled by 2019 GDP. Heat damage is the sum of these three components. 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). Hot days is the actual average number of hot days per year between 2011-2020. Δ Hot days is the change in the average number of actual hot days between 2001-2010 and 2011-2020. Panel B presents the rank correlations for the risk measures and the two historical temperature measures.

Panel A: Summary statistics

	N	Mean	Std	Min	25%	Median	75%	Max
Heat damage (bps of GDP)	3143	83.23	39.19	-51.98	62.59	86.94	104.64	185.98
Energy damage	3143	58.34	31.60	-60.34	44.37	59.90	77.14	146.58
High-risk labor	3143	14.15	5.15	-4.33	11.22	14.42	17.02	30.51
Low-risk labor	3143	10.74	5.28	-20.57	6.60	10.50	13.75	63.17
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
Hot days	3107	3.12	8.10	0.00	0.00	0.40	1.60	116.80

Panel B: Correlations

	Heat damage	Energy damage	High-risk labor	Low-risk labor	Heat score	Hot days	Δ Hot days	Δ Proj Hot days
Heat damage	1.00	0.98	0.85	0.68	0.59	0.82	0.35	0.68
Energy damage	0.98	1.00	0.79	0.57	0.60	0.75	0.37	0.64
High-risk labor	0.85	0.79	1.00	0.63	0.50	0.70	0.36	0.58
Low-risk labor	0.68	0.57	0.63	1.00	0.25	0.88	0.12	0.65
Heat score	0.59	0.60	0.50	0.25	1.00	0.41	0.40	0.47
Δ Proj Hot days	0.82	0.75	0.70	0.88	0.41	1.00	0.19	0.73
Δ Hot days	0.35	0.37	0.36	0.12	0.40	0.19	1.00	0.38
Hot days	0.68	0.64	0.58	0.65	0.47	0.73	0.38	1.00

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)	99490	68.75	59.50	0.00	32.11	54.91	83.62	555.83
High rating	70464	52.50	39.11	0.00	27.35	47.08	67.88	555.77
Low rating	29026	108.21	78.90	0.04	54.48	88.26	139.81	555.83
Time to maturity	99490	12.19	7.38	1.00	6.34	11.18	16.85	49.66
Credit rating	99490	3.91	2.44	1.00	2.00	3.00	5.00	19.00
Turnover	99490	0.86	1.22	0.00	0.12	0.31	1.02	5.40
Std(Price)	99490	0.89	0.64	0.00	0.36	0.85	1.31	3.95
Callable	99490	0.82	0.39	0.00	1.00	1.00	1.00	1.00
GO	99490	0.43	0.50	0.00	0.00	0.00	1.00	1.00
Energy expenditures	99490	3.87	0.98	2.38	3.29	3.65	4.27	13.05
Heat damage	99490	0.77	0.37	-0.29	0.57	0.72	0.99	1.86
High rating	70464	0.73	0.36	-0.29	0.56	0.69	0.95	1.86
Low rating	29026	0.85	0.36	-0.23	0.63	0.89	1.05	1.84
Panel B: Corporate bonds								
Spread (bps)	543004	156.79	140.29	0.00	78.23	122.40	190.69	2411.72
High rating	504398	142.33	119.33	0.00	75.34	116.02	173.82	2395.81
Low rating	38606	345.66	229.01	0.42	221.55	297.03	399.71	2411.72
Time to maturity	543004	10.51	10.20	1.00	3.50	6.74	16.22	99.79
Credit rating	543004	7.56	2.36	1.00	6.00	8.00	9.00	21.00
Turnover	543004	0.67	0.69	0.00	0.21	0.44	0.85	3.71
Std(Price)	543004	1.01	0.96	0.00	0.41	0.75	1.31	9.56
Callable	543004	0.78	0.42	0.00	1.00	1.00	1.00	1.00
Heat score	543004	44.28	7.47	21.72	40.14	42.89	47.58	70.72
High rating	504398	44.20	7.51	21.72	40.08	42.76	47.46	70.72
Low rating	38606	45.29	6.77	21.78	41.90	43.84	48.46	68.19
Panel C: Equities								
$E_t(R^e_{t+1})$ (bps)	77214	451.58	540.32	0.02	146.25	289.62	550.00	5428.83
Beta	76856	1.06	0.37	-0.25	0.82	1.03	1.27	3.55
Size ($B)	77214	31.33	66.51	0.11	6.74	13.18	28.25	2255.97
B/M	76390	0.47	0.70	-60.61	0.21	0.36	0.65	6.80
Profitability	75934	0.65	15.64	-13.33	0.18	0.28	0.41	1417.33
Investment	75412	0.13	0.42	-0.73	0.00	0.06	0.14	12.56
$R_{t-11,t}$	76403	0.15	0.36	-0.97	-0.05	0.13	0.31	7.91
Heat score	77214	42.91	7.34	20.09	38.30	42.20	45.63	70.72

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, 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.

Risk	Heat damage (% GDP)				Heat score			
Risk×I_{2007}	-1.60	(5.79)	-1.70	(5.41)	2.54	(2.45)	1.20	(1.93)
Risk×I_{2008}	13.54	(9.72)	8.39	(8.23)	-0.16	(5.49)	1.90	(2.50)
Risk×I_{2009}	34.08**	(16.16)	21.10**	(10.42)	-1.62	(7.33)	1.83	(3.89)
Risk×I_{2010}	10.87	(9.99)	6.98	(9.43)	-0.37	(5.32)	-0.29	(3.73)
Risk×I_{2011}	3.76	(10.37)	9.11	(9.34)	1.57	(5.29)	-1.31	(4.01)
Risk×I_{2012}	9.23	(9.55)	17.17**	(8.12)	4.50	(4.97)	4.17	(3.77)
Risk×I_{2013}	16.41*	(9.20)	17.69**	(7.61)	8.15*	(4.68)	6.55*	(3.37)
Risk×I_{2014}	17.49*	(9.16)	16.04**	(7.62)	9.71**	(4.67)	7.45**	(3.27)
Risk×I_{2015}	20.71**	(9.49)	19.65**	(7.59)	10.73**	(4.62)	8.28**	(3.30)
Risk×I_{2016}	21.84**	(9.67)	21.26***	(7.43)	10.57**	(4.67)	8.68***	(3.26)
Risk×I_{2017}	21.02**	(9.37)	20.23***	(7.31)	9.39**	(4.65)	7.64**	(3.15)
Risk×I_{2018}	20.34**	(9.45)	20.58***	(7.58)	9.86**	(4.68)	8.35***	(3.17)
Risk×I_{2019}	19.64**	(9.72)	19.01**	(7.41)	9.77**	(4.70)	8.03**	(3.19)
Risk×I_{2020}	20.67*	(10.51)	16.64**	(7.56)	9.81**	(4.79)	5.80*	(3.23)
N	99490		99490		99490		99490	
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. Panel A presents the average covariates for the two samples. Panel B 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	0.30	1.25	-1.24
Coupon	3.89	3.87	3.55	3.56
Time to maturity	13.20	12.74	11.27	11.11
County population	835.29	631.27	558.63	502.80
Income per capita	44.68	47.82	44.00	45.86
Unemployment rate	5.71	5.85	5.50	5.69
Rating	4.48	4.48	4.32	4.32

Panel B: Regression coefficients

Risk	Heat damage (% GDP)		Heat score	
I_{2007}	6.29	(7.99)	6.45	(6.65)
I_{2008}	3.02	(13.38)	4.07	(13.11)
I_{2009}	5.56	(15.26)	18.54	(16.23)
I_{2010}	8.73	(10.55)	10.97	(10.43)
I_{2011}	-0.64	(11.74)	8.10	(13.01)
I_{2012}	24.44^{**}	(9.90)	16.78^{*}	(10.05)
I_{2013}	21.62^{**}	(8.66)	25.65^{***}	(9.21)
I_{2014}	24.57^{***}	(8.90)	31.46^{***}	(9.02)
I_{2015}	29.21^{***}	(9.71)	35.19^{***}	(8.97)
I_{2016}	27.33^{***}	(8.76)	31.47^{***}	(8.57)
I_{2017}	30.69^{***}	(9.08)	25.39^{***}	(8.98)
I_{2018}	30.32^{***}	(8.92)	24.04^{***}	(8.65)
I_{2019}	29.67^{***}	(8.80)	25.41^{***}	(8.52)
I_{2020}	27.00^{**}	(11.68)	18.58^{*}	(10.69)
N	20148		19973	
R^2	0.09		0.09	
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$\times I_{2007}$	3.30	(5.37)	-10.72	(12.70)	-8.63	(9.59)	10.48	(6.65)	4.80	(7.46)	0.99	(8.58)
Heat dmg$\times I_{2008}$	0.89	(9.15)	21.69	(16.05)	-12.53	(11.78)	25.43**	(11.17)	1.00	(7.36)	18.26	(12.71)
Heat dmg$\times I_{2009}$	5.46	(10.91)	39.45**	(18.08)	-2.72	(12.98)	38.71***	(12.84)	-2.00	(8.65)	37.66**	(14.54)
Heat dmg$\times I_{2010}$	-1.77	(10.12)	18.00	(17.91)	-15.72	(13.41)	25.47**	(10.52)	-9.72	(6.96)	19.10	(14.43)
Heat dmg$\times I_{2011}$	2.21	(9.23)	10.84	(17.76)	-6.03	(11.66)	25.03**	(12.22)	-17.86**	(7.12)	22.98	(14.80)
Heat dmg$\times I_{2012}$	11.81	(9.78)	16.51	(16.81)	3.47	(11.37)	31.54***	(9.28)	-0.15	(6.22)	24.34*	(13.35)
Heat dmg$\times I_{2013}$	10.76	(9.65)	18.61	(15.47)	2.75	(10.04)	31.62***	(8.97)	-7.61	(6.13)	28.84**	(11.65)
Heat dmg$\times I_{2014}$	8.97	(9.74)	19.87	(15.59)	1.54	(10.53)	29.18***	(8.59)	-10.10	(6.16)	30.04**	(11.80)
Heat dmg$\times I_{2015}$	10.98	(9.91)	28.68*	(15.30)	-1.79	(10.51)	37.13***	(8.31)	-5.42	(6.11)	31.61***	(11.36)
Heat dmg$\times I_{2016}$	11.96	(9.96)	33.44**	(15.83)	1.74	(10.48)	37.63***	(8.63)	-2.85	(5.94)	32.56***	(11.57)
Heat dmg$\times I_{2017}$	12.10	(9.76)	26.45*	(15.12)	0.26	(10.47)	37.65***	(8.23)	-6.43	(6.19)	34.45***	(10.88)
Heat dmg$\times I_{2018}$	11.88	(10.02)	30.68*	(15.72)	6.01	(10.25)	34.99***	(8.68)	-8.45	(6.05)	39.44***	(11.49)
Heat dmg$\times I_{2019}$	9.91	(9.87)	31.33**	(14.83)	2.48	(10.28)	33.51***	(8.46)	-6.33	(5.97)	33.34***	(11.20)
Heat dmg$\times I_{2020}$	9.27	(10.13)	17.87	(14.25)	2.09	(10.39)	30.71***	(8.65)	-6.45	(6.41)	26.51**	(11.81)
N	70464		29026		43289		56201		43186		53287	
R^2	0.34		0.67		0.65		0.62		0.43		0.64	
County & Time FE	Y											
Controls	Y											
Rating x Year FE	Y											

Table 6: Heat damage components 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, and credit-rating fixed effects. Standard errors are two-way clustered by county and month. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Risk	Energy damage		High-risk labor		Low-risk labor		Δ Proj Hot days	
Risk×I_{2007}	-0.60	(7.32)	-21.80	(33.59)	29.64	(25.63)	0.08	(0.08)
Risk×I_{2008}	8.82	(10.80)	53.66	(45.24)	101.57**	(41.59)	0.22*	(0.12)
Risk×I_{2009}	19.36	(13.32)	125.71*	(65.38)	222.69***	(65.24)	0.46***	(0.17)
Risk×I_{2010}	4.78	(11.79)	89.05	(61.71)	109.17*	(55.69)	0.15	(0.15)
Risk×I_{2011}	3.30	(12.49)	129.54**	(56.05)	163.62***	(49.19)	0.26*	(0.16)
Risk×I_{2012}	15.68	(10.64)	154.10***	(51.64)	160.39***	(51.35)	0.40***	(0.14)
Risk×I_{2013}	17.60*	(10.15)	165.15***	(46.62)	139.25***	(45.84)	0.35***	(0.13)
Risk×I_{2014}	15.77	(10.06)	150.79***	(46.36)	135.67***	(48.20)	0.27**	(0.13)
Risk×I_{2015}	20.91**	(10.02)	158.71***	(45.75)	142.08***	(50.01)	0.30**	(0.13)
Risk×I_{2016}	24.62**	(9.82)	147.94***	(45.09)	130.38**	(50.54)	0.32**	(0.13)
Risk×I_{2017}	22.62**	(9.64)	155.57***	(44.85)	131.64***	(49.59)	0.33**	(0.13)
Risk×I_{2018}	23.34**	(9.94)	158.31***	(46.19)	125.82**	(51.88)	0.31**	(0.13)
Risk×I_{2019}	21.44**	(9.73)	144.47***	(45.69)	124.50**	(51.66)	0.30**	(0.13)
Risk×I_{2020}	19.57*	(9.98)	87.10*	(45.78)	126.57**	(53.58)	0.23*	(0.13)
N	99490		99490		99490		99319	
R^2	0.61		0.61		0.61		0.61	
County & Time FE		Y						
Controls		Y						
Rating x Year FE		Y						

Table 7: Heat score and corporate bond spreads

Panel A

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, 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.

y-variable	Spread						OAS			
Sample	Full sample		High rating		Low rating		High rating		Low rating	
Heat score×I_{2007}	0.07	(0.52)	-0.94***	(0.11)	5.44	(3.75)	-0.25	(1.11)	3.47	(7.41)
Heat score×I_{2008}	-22.62***	(7.28)	-22.97***	(7.98)	-30.90	(19.19)	-12.71**	(5.55)	-24.78	(16.80)
Heat score×I_{2009}	-36.81**	(14.66)	-36.76**	(14.71)	-39.04	(25.24)	-22.40***	(6.86)	1.50	(18.34)
Heat score×I_{2010}	-3.67	(3.92)	-6.48*	(3.89)	35.08**	(14.35)	-3.01	(3.58)	6.21	(8.38)
Heat score×I_{2011}	-5.35	(3.79)	-8.73**	(3.84)	40.57**	(15.92)	-5.92*	(3.32)	3.80	(10.54)
Heat score×I_{2012}	-5.91*	(3.31)	-8.68**	(3.44)	45.10***	(16.85)	-7.26**	(3.13)	2.61	(10.75)
Heat score×I_{2013}	-1.88	(2.22)	-4.15*	(2.26)	43.66***	(16.01)	-2.72	(2.17)	25.02***	(9.38)
Heat score×I_{2014}	0.83	(2.05)	-1.76	(2.01)	44.03***	(15.89)	0.02	(1.90)	15.72*	(8.53)
Heat score×I_{2015}	2.13	(2.59)	-0.71	(2.47)	52.57***	(17.90)	1.72	(2.17)	19.74**	(9.50)
Heat score×I_{2016}	2.58	(2.78)	-0.06	(2.69)	51.94***	(16.35)	1.34	(2.61)	32.62***	(9.03)
Heat score×I_{2017}	1.55	(2.22)	-0.57	(2.10)	40.76***	(15.10)	1.41	(2.35)	20.88**	(8.98)
Heat score×I_{2018}	-0.55	(2.17)	-2.30	(2.10)	33.78**	(14.90)	0.61	(2.24)	12.73	(10.33)
Heat score×I_{2019}	0.49	(2.24)	-1.09	(2.21)	34.59**	(15.03)	0.36	(2.40)	10.24	(9.60)
Heat score×I_{2020}	2.93	(2.82)	1.46	(2.82)	32.99**	(15.85)	3.41	(3.19)	25.14*	(13.32)
N	543004		504398		38606		46425		5602	
R^2	0.71		0.64		0.81		0.81		0.86	
Firm & Time FE	Y									
Controls	Y									
Rating x Year FE	Y									

Table 7 (cont'd)

Panel B

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

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

where the dependent variable is expected default frequency from Moody's KMV (EDF) with different maturities (1, 2, 5, and 10 years), and $\gamma_{c,t}$ are credit rating dummies. High-rating (low rating) subsample includes only investment grade (non-investment grade) bonds. 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.

Sample	High rating		Low rating							
y-variable	EDF10		EDF1		EDF2		EDF5		EDF10	
Heat score×I_{2007}	-0.27	(0.65)	-1.43	(3.67)	3.20	(3.43)	8.47	(6.00)	9.85*	(5.43)
Heat score×I_{2008}	-0.09	(1.24)	-11.64*	(6.98)	-2.17	(5.44)	7.91	(6.34)	14.03**	(6.76)
Heat score×I_{2009}	1.95	(1.40)	-21.98	(22.43)	-4.47	(14.34)	16.29	(10.31)	21.71***	(8.08)
Heat score×I_{2010}	2.48**	(1.20)	-0.51	(6.97)	10.11	(7.06)	22.68**	(10.32)	25.08***	(8.72)
Heat score×I_{2011}	0.47	(1.25)	0.12	(4.99)	10.09*	(5.84)	27.75***	(9.21)	29.95***	(8.44)
Heat score×I_{2012}	0.08	(1.24)	-0.07	(5.16)	9.39*	(5.37)	29.33***	(8.98)	30.15***	(8.06)
Heat score×I_{2013}	0.61	(1.21)	3.58	(5.62)	11.06*	(6.37)	34.95***	(10.08)	35.31***	(9.08)
Heat score×I_{2014}	1.09	(1.30)	1.86	(6.52)	9.31	(7.16)	31.36***	(10.23)	31.61***	(9.38)
Heat score×I_{2015}	4.22***	(1.29)	6.32	(6.82)	14.49*	(7.51)	35.90***	(10.81)	36.59***	(9.63)
Heat score×I_{2016}	5.78***	(1.39)	9.25	(6.78)	20.84***	(7.89)	40.31***	(12.18)	42.73***	(11.36)
Heat score×I_{2017}	6.33***	(1.63)	11.20	(6.99)	22.08***	(7.84)	47.36***	(13.96)	49.29***	(12.19)
Heat score×I_{2018}	6.28***	(1.61)	9.86	(6.53)	22.02***	(7.55)	36.07***	(12.21)	41.83***	(11.85)
Heat score×I_{2019}	6.26***	(1.55)	9.66	(6.58)	19.37***	(6.99)	26.07**	(13.01)	31.29***	(11.76)
Heat score×I_{2020}	7.05***	(1.87)	23.54*	(14.18)	28.97**	(11.76)	32.79**	(12.61)	39.90***	(10.64)
N	46235		6258		6254		7041		7146	
R^2	0.90		0.58		0.65		0.72		0.79	
Firm & Time FE	Y									
Rating x Year FE	Y									

Table 7 (cont'd)

Panel C

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. High-rating (low rating) subsample includes only investment grade (non-investment grade) bonds. 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.

Sample	High rating				Low rating			
x-var	Heat score		EDF		Heat score		EDF	
x-var			-26.62**	(11.88)			14.99	(14.97)
x-var$\times I_{2007}$	4.84***	(1.32)	25.51***	(7.39)	2.05	(6.09)	-10.77	(9.61)
x-var$\times I_{2008}$	6.81	(5.92)	98.43***	(18.77)	-29.43	(21.89)	63.65***	(14.50)
x-var$\times I_{2009}$	-10.27	(12.26)	63.20***	(21.82)	-33.56	(29.60)	58.13**	(22.88)
x-var$\times I_{2010}$	9.84***	(3.24)	86.76***	(8.42)	21.53*	(11.51)	20.51	(12.47)
x-var$\times I_{2011}$	8.07**	(3.17)	94.05***	(12.57)	23.49	(15.25)	-2.88	(12.36)
x-var$\times I_{2012}$	8.70***	(3.09)	99.24***	(12.79)	33.76*	(18.05)	48.65**	(19.92)
x-var$\times I_{2013}$	3.25	(2.63)	47.74***	(8.80)	27.61*	(15.29)	14.59	(18.95)
x-var$\times I_{2014}$	1.58	(2.32)	31.71***	(7.96)	25.78*	(14.34)	10.54	(18.47)
x-var$\times I_{2015}$	5.18*	(3.05)	35.45***	(9.08)	32.30*	(16.82)	9.65	(16.92)
x-var$\times I_{2016}$	9.13***	(3.47)	53.09***	(11.00)	32.41**	(15.42)	31.41**	(15.89)
x-var$\times I_{2017}$	2.02	(2.66)	29.72***	(7.59)	24.43*	(14.45)	5.53	(14.94)
x-var$\times I_{2018}$	-0.87	(2.67)	23.76***	(7.38)	17.20	(15.39)	1.83	(14.95)
x-var$\times I_{2019}$	1.40	(2.78)	28.32***	(7.55)	18.16	(15.31)	3.56	(15.67)
x-var$\times I_{2020}$	10.75***	(3.82)	62.37***	(11.01)	23.94	(16.60)	30.79*	(17.98)
N	470117				36111			
R^2	0.64				0.83			
Firm & Time FE	Y							
Controls	Y							
EDF x Year	Y							

Table 8: Heat score 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. Balanced panel only includes companies that have data available during the whole sample period. $\beta^* \in [0,2]$ only includes observations for which β^* is sufficiently close to 1 to mitigate measurement error in $E_t R^e_{i,t+1}$ caused by linearization (see Section I of Online Appendix to Martin and Wagner, 2019). $E_t(R_{t+1\to t+12})$ uses 1-year expected return as y-variable. Last column 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.

y-variable	$E_t(R_{t+1})$								$E_t(R_{t+1\to t+12})$		$E_t(R_{t+1})(1-L_t)$	
Sample	Full sample				Balanced panel		$\beta^* \in [0,2]$		Full sample		Full sample	
Heat score$\times I_{2007}$	0.53	(7.22)	4.64	(10.11)	7.29	(9.80)	-7.63	(6.81)	5.29	(7.86)	-3.12	(8.08)
Heat score$\times I_{2008}$	-18.84	(21.93)	-19.89	(22.82)	-27.16	(22.78)	-48.90***	(16.64)	-12.83	(15.42)	-37.24*	(21.67)
Heat score$\times I_{2009}$	-18.00	(25.98)	-26.46	(24.13)	-31.65	(22.82)	-36.84***	(12.79)	-25.99	(19.08)	-46.42***	(16.51)
Heat score$\times I_{2010}$	6.55	(9.35)	-6.22	(7.95)	-8.24	(7.83)	-16.79***	(6.42)	-5.38	(6.58)	-15.33**	(7.58)
Heat score$\times I_{2011}$	1.04	(10.33)	1.88	(9.43)	-2.63	(9.48)	-12.89	(8.57)	5.89	(6.94)	-15.73*	(8.53)
Heat score$\times I_{2012}$	12.01	(9.13)	20.13**	(8.70)	21.16**	(8.95)	7.99	(5.72)	11.33*	(6.56)	9.51	(7.31)
Heat score$\times I_{2013}$	23.44**	(9.05)	22.84***	(8.08)	25.25***	(8.13)	6.90	(5.30)	17.98***	(6.81)	16.43**	(6.95)
Heat score$\times I_{2014}$	18.78*	(10.80)	40.85***	(11.54)	38.95***	(10.79)	17.89**	(7.29)	34.91***	(8.26)	28.95***	(9.07)
Heat score$\times I_{2015}$	46.09***	(11.38)	41.23***	(10.57)	38.96***	(10.14)	18.52***	(6.76)	35.90***	(7.53)	30.84***	(8.19)
Heat score$\times I_{2016}$	43.13***	(12.89)	52.14***	(10.47)	55.96***	(10.36)	34.00***	(7.63)	47.28***	(7.45)	38.00***	(8.26)
Heat score$\times I_{2017}$	27.51**	(12.56)	40.70***	(11.63)	49.37***	(10.85)	27.32***	(7.07)	50.06***	(8.14)	32.29***	(9.02)
Heat score$\times I_{2018}$	20.95*	(11.79)	40.33***	(10.53)	51.28***	(10.35)	18.68***	(6.57)	45.83***	(8.24)	30.09***	(8.08)
Heat score$\times I_{2019}$	25.47*	(13.05)	56.59***	(12.85)	63.86***	(12.70)	34.47***	(7.87)	56.10***	(9.40)	42.17***	(9.65)
Heat score$\times I_{2020}$	88.00***	(28.22)	57.93**	(23.35)	45.62**	(22.73)	5.05	(8.92)	41.97***	(13.29)	23.06	(16.57)
N	77214		74899		65755		55145		77672		74633	
R^2	0.66		0.70		0.71		0.85		0.71		0.70	
Firm & Time FE	Y		Y		Y		Y		Y		Y	
Controls	N		Y		Y		Y		Y		Y	

Table 9: Heat score 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, and firm's energy expenditures as a fraction of its revenue, 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.

y-variable	Spread						OAS			
Sample	Full sample		High rating		Low rating		High rating		Low rating	
Heat score×I_{2007}	0.68	(0.74)	-0.44	(0.46)	12.75***	(4.34)	1.36	(1.25)	2.43	(8.04)
Heat score×I_{2008}	-20.69***	(7.17)	-21.79***	(7.88)	-8.80	(18.91)	-8.27	(5.60)	-11.64	(17.00)
Heat score×I_{2009}	-34.76**	(14.52)	-35.57**	(14.48)	-49.24	(30.12)	-18.77***	(6.82)	1.52	(20.01)
Heat score×I_{2010}	-3.05	(3.91)	-5.82	(3.89)	32.77**	(16.31)	-0.52	(3.51)	3.42	(9.94)
Heat score×I_{2011}	-4.80	(3.82)	-8.35**	(3.86)	40.70**	(18.12)	-2.81	(3.27)	2.25	(10.55)
Heat score×I_{2012}	-5.33	(3.33)	-8.22**	(3.42)	45.40**	(19.32)	-4.31	(3.17)	-1.70	(10.85)
Heat score×I_{2013}	-1.48	(2.29)	-3.76	(2.32)	40.44**	(18.95)	-0.52	(2.32)	17.60*	(9.65)
Heat score×I_{2014}	1.20	(2.14)	-1.39	(2.10)	44.59**	(18.59)	2.30	(2.02)	10.67	(8.80)
Heat score×I_{2015}	2.23	(2.67)	-0.57	(2.59)	52.42***	(19.51)	3.55	(2.23)	11.99	(9.23)
Heat score×I_{2016}	2.46	(2.86)	-0.10	(2.80)	49.49***	(18.04)	2.77	(2.70)	26.46***	(9.14)
Heat score×I_{2017}	1.90	(2.29)	-0.09	(2.16)	39.66**	(17.21)	3.38	(2.43)	14.95*	(8.75)
Heat score×I_{2018}	0.03	(2.24)	-1.62	(2.15)	34.11**	(17.07)	2.76	(2.35)	6.00	(9.60)
Heat score×I_{2019}	1.11	(2.29)	-0.36	(2.23)	36.26**	(17.26)	2.35	(2.56)	3.23	(9.57)
N	503211		467752		35459		43412		5275	
R^2	0.71		0.64		0.82		0.82		0.86	
Firm & Time FE	Y									
Controls	Y									
Rating x Year FE	Y									

Table 10: Heat score 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, past 12-month returns, and firm's energy expenditures as a fraction of its revenue. Balanced panel only includes companies that have data available during the whole sample period. $\beta^* \in [0,2]$ only includes observations for which β^* is sufficiently close to 1 to mitigate measurement error in $E_t R^e_{i,t+1}$ caused by linearization (see Section I of Online Appendix to Martin and Wagner, 2019). $E_t(R_{t+1\to t+12})$ uses 1-year expected return as y-variable. Last column 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.

y-variable	$E_t(R_{t+1})$								$E_t(R_{t+1\to t+12})$		$E_t(R_{t+1})(1-L_t)$	
Sample	Full sample				Balanced panel		$\beta^* \in [0,2]$		Full sample		Full sample	
Heat score$\times I_{2007}$	-0.75	(7.28)	1.80	(9.55)	4.15	(9.27)	-7.74	(6.69)	4.25	(7.59)	-4.93	(7.85)
Heat score$\times I_{2008}$	-19.36	(22.01)	-23.93	(22.56)	-32.05	(22.46)	-49.08***	(16.68)	-15.01	(15.15)	-40.02*	(21.51)
Heat score$\times I_{2009}$	-18.96	(26.15)	-27.07	(24.32)	-33.04	(23.02)	-35.37***	(12.91)	-25.46	(19.41)	-46.35***	(16.77)
Heat score$\times I_{2010}$	5.57	(9.39)	-6.82	(7.74)	-9.08	(7.62)	-16.15**	(6.39)	-5.21	(6.49)	-15.68**	(7.48)
Heat score$\times I_{2011}$	0.65	(10.38)	-1.66	(9.08)	-6.53	(9.16)	-13.17	(8.57)	4.00	(6.77)	-17.93**	(8.39)
Heat score$\times I_{2012}$	11.66	(9.09)	16.17*	(8.34)	16.63*	(8.56)	7.04	(5.76)	9.18	(6.42)	7.16	(7.21)
Heat score$\times I_{2013}$	23.32***	(8.95)	19.94**	(7.72)	21.87***	(7.82)	6.37	(5.31)	16.12**	(6.68)	14.46**	(6.81)
Heat score$\times I_{2014}$	19.01*	(10.59)	36.73***	(11.14)	34.24***	(10.38)	17.42**	(7.33)	32.66***	(8.19)	26.52***	(8.93)
Heat score$\times I_{2015}$	45.76***	(11.10)	40.84***	(9.98)	37.54***	(9.62)	18.91***	(6.71)	36.44***	(7.22)	30.51***	(7.86)
Heat score$\times I_{2016}$	43.58***	(12.46)	51.24***	(10.05)	53.36***	(9.98)	34.15***	(7.67)	47.55***	(7.18)	37.54***	(7.99)
Heat score$\times I_{2017}$	30.05**	(12.20)	41.16***	(10.77)	47.36***	(10.26)	28.58***	(7.00)	49.81***	(7.77)	32.50***	(8.62)
Heat score$\times I_{2018}$	22.94**	(11.47)	38.56***	(9.94)	46.39***	(10.00)	19.86***	(6.63)	44.60***	(8.00)	29.21***	(7.80)
Heat score$\times I_{2019}$	26.49**	(12.57)	52.59***	(12.11)	57.09***	(12.19)	35.18***	(7.99)	54.15***	(9.13)	40.09***	(9.23)
N	71764		69278		60998		50861		72003		69046	
R^2	0.67		0.71		0.72		0.84		0.72		0.71	
Firm & Time FE	Y		Y		Y		Y		Y		Y	
Controls	N		Y		Y		Y		Y		Y	

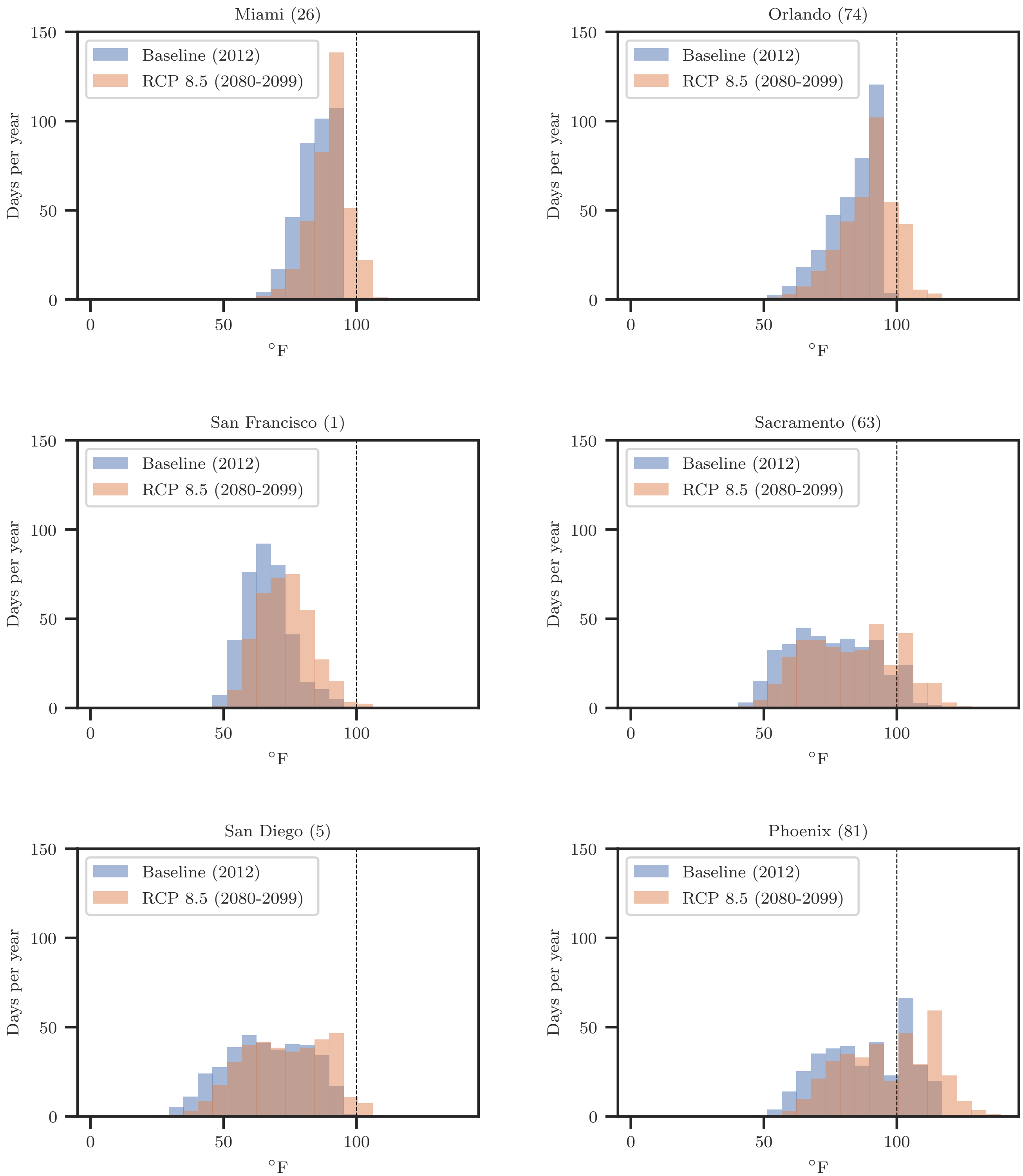
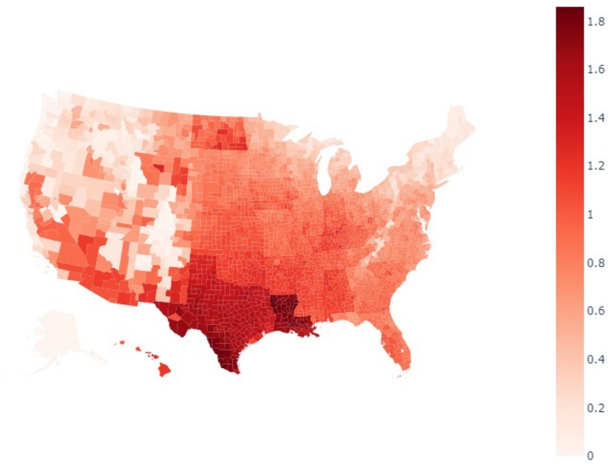
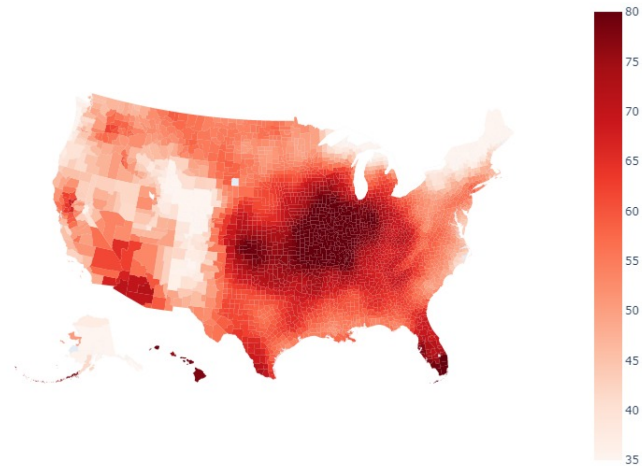


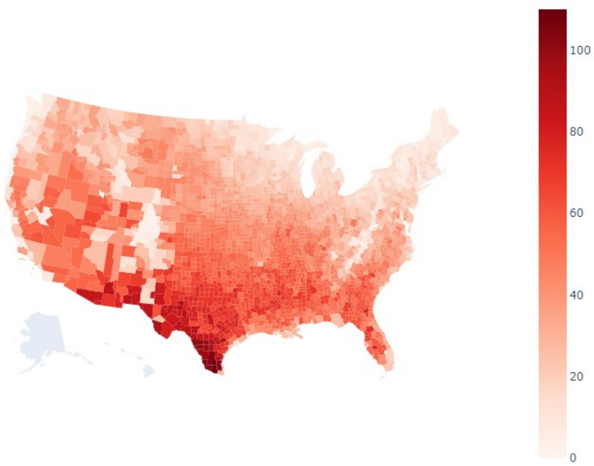
Figure 2: **Annual temperature distributions under Baseline and RCP 8.5 scenarios.** Counties' percentile ranks in terms of an increase in the number of +100°F days are shown in parentheses.



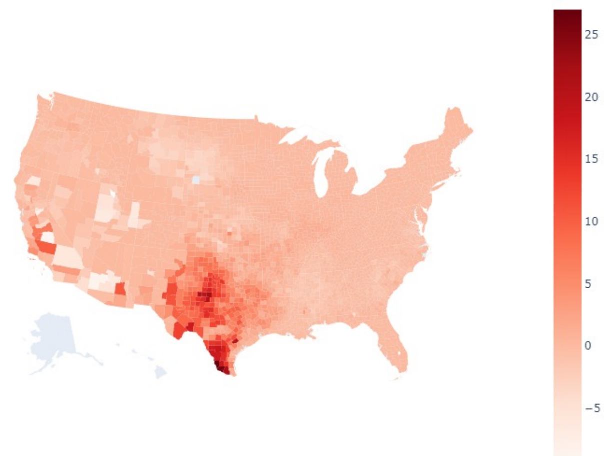
(a) Heat damage (% GDP)



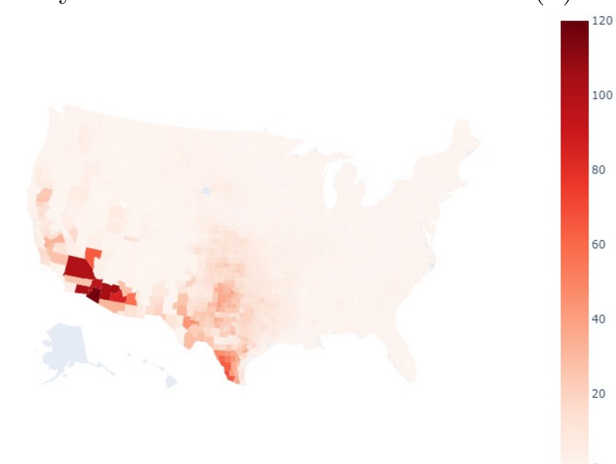
(b) Heat score



(c) Δ Proj Hot days

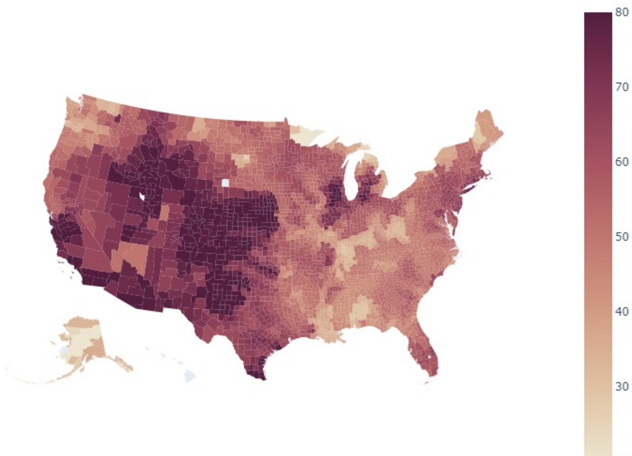


(d) Δ Hot days

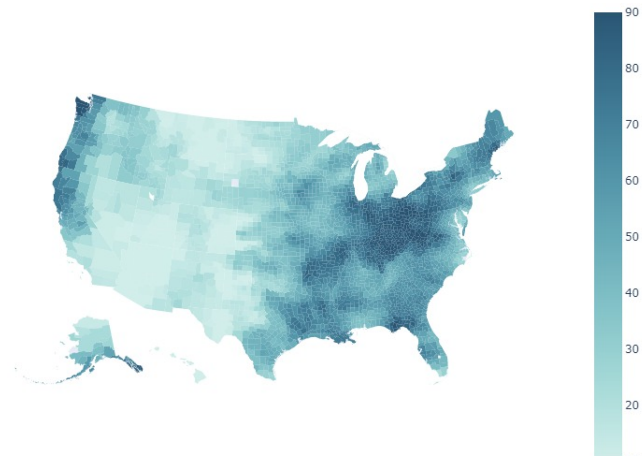


(e) Hot days

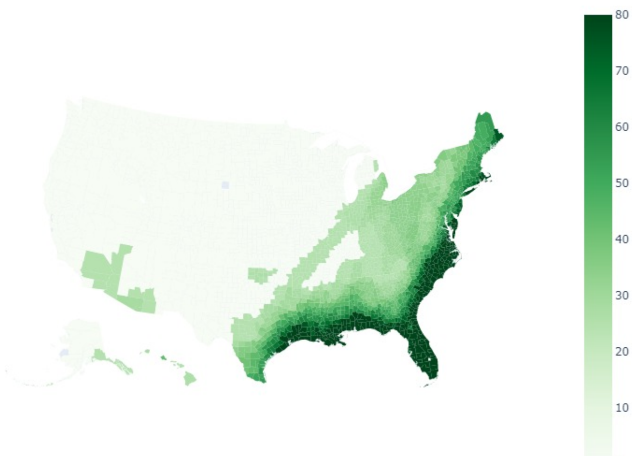
Figure 3: **Physical risk exposure by county.** The figure shows geographical distribution of measures of physical risk exposure.



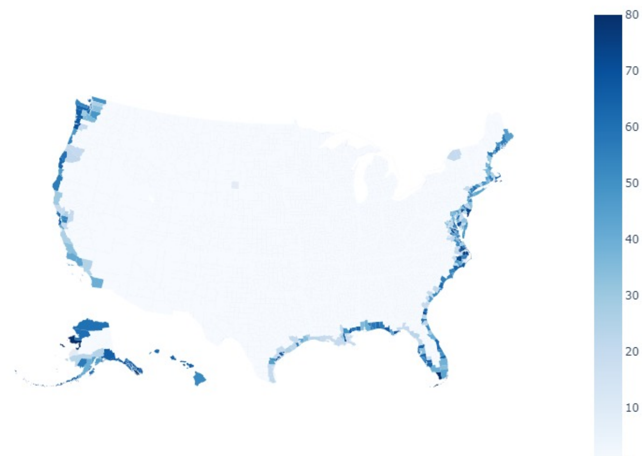
(f) Water score



(g) Rainfall score



(h) Hurricane score



(i) Sealevel score

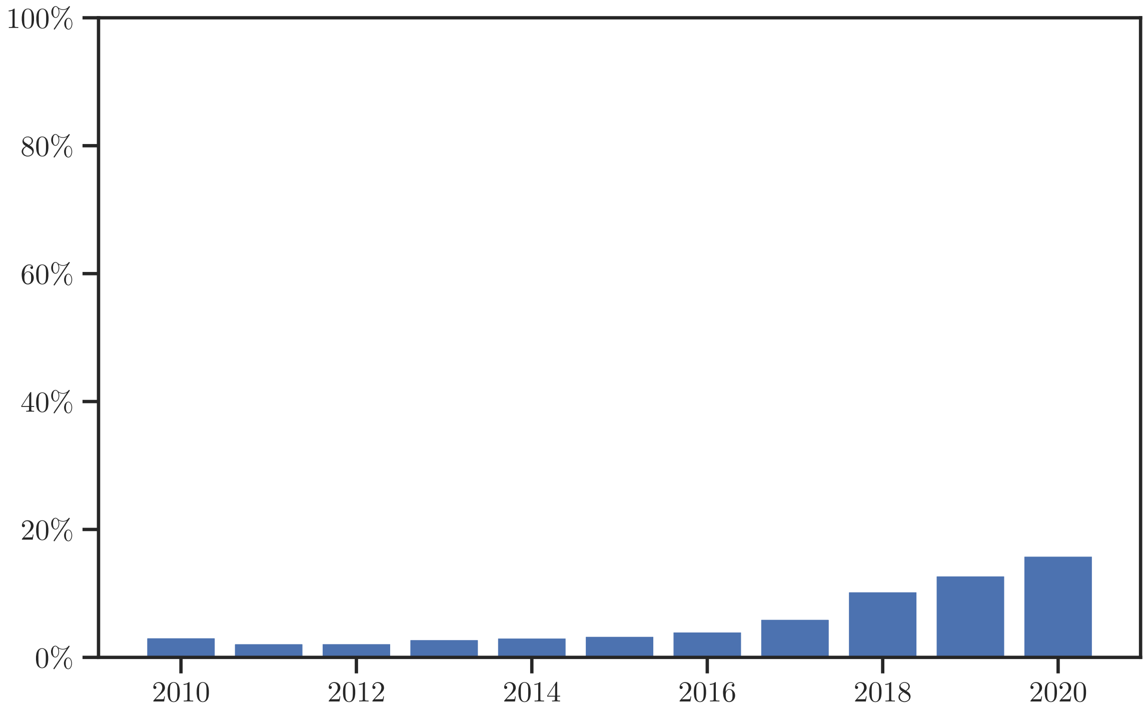


Figure 4: **Fraction of municipal bond prospectuses mentioning "climate change".** The figure shows year-by-year the fraction of municipal bond prospectuses that contain the phrase "climate change" at least once in the document.

Online appendix to

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

Appendix A: Additional tests and robustness

Oster (2019) Tests

Oster (2019) develops a methodology to evaluate the potential impact of omitted 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.

This 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.

Table A1 presents Oster (2019) δ for our main municipal bond results. The average δ after 2013 is around 2, implying that the unobservable credit factors would need to be around twice as important as the ones captured by credit ratings in order to produce α_y of zero. Overall, we find this unlikely. For example, Oster (2019) suggests that in many applications, a value of δ=1 seems an appropriate cutoff to argue that omitted variables are unlikely to drive the results.[36]

[36]Note that when implementing the method, the researcher needs to take a stance on how much of the

Table A2 presents the results for corporate bonds. When using our main high-yield corporate bond sample, the average δ is again around 2. For option-adjusted spread sample from Morgan Stanley Research, the δ's are again large in magnitude, but sometimes negative. This occurs whenever the inclusion of controls makes the estimate stronger, in which case the unobserved variables would need to be negatively correlated with observarbles to produce α_y of zero. With values that are generally larger than 1 in magnitude, we again conclude that unoservable credit factors are unlikley to explain our results.

remaining variation in dependent variable the unobservables could explain at most. We set R_max=1, which gives us the most conservative estimates for δ. Under more realistic assumptions with R_max¡1, our δ estimates would be higher in magnitude.

Table A1: Heat stress and muni bond spreads with Oster (2019) δ

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. 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}	-1.60	(5.79)	-1.70	(5.41)	1.78	2.54	(2.45)	1.20	(1.93)	0.47
Risk×I_{2008}	13.54	(9.72)	8.39	(8.23)	0.52	-0.16	(5.49)	1.90	(2.50)	-0.54
Risk×I_{2009}	34.08**	(16.16)	21.10**	(10.42)	0.57	-1.62	(7.33)	1.83	(3.89)	-0.31
Risk×I_{2010}	10.87	(9.99)	6.98	(9.43)	0.58	-0.37	(5.32)	-0.29	(3.73)	1.78
Risk×I_{2011}	3.76	(10.37)	9.11	(9.34)	-1.28	1.57	(5.29)	-1.31	(4.01)	-0.26
Risk×I_{2012}	9.23	(9.55)	17.17**	(8.12)	-1.74	4.50	(4.97)	4.17	(3.77)	4.13
Risk×I_{2013}	16.41*	(9.20)	17.69**	(7.61)	4.97	8.15*	(4.68)	6.55*	(3.37)	1.87
Risk×I_{2014}	17.49*	(9.16)	16.04**	(7.62)	2.00	9.71**	(4.67)	7.45**	(3.27)	1.56
Risk×I_{2015}	20.71**	(9.49)	19.65**	(7.59)	2.41	10.73**	(4.62)	8.28**	(3.30)	1.58
Risk×I_{2016}	21.84**	(9.67)	21.26***	(7.43)	2.57	10.57**	(4.67)	8.68***	(3.26)	1.98
Risk×I_{2017}	21.02**	(9.37)	20.23***	(7.31)	2.39	9.39**	(4.65)	7.64**	(3.15)	1.95
Risk×I_{2018}	20.34**	(9.45)	20.58***	(7.58)	3.36	9.86**	(4.68)	8.35***	(3.17)	2.40
Risk×I_{2019}	19.64**	(9.72)	19.01**	(7.41)	2.89	9.77**	(4.70)	8.03**	(3.19)	2.09
Risk×I_{2020}	20.67*	(10.51)	16.64**	(7.56)	1.23	9.81**	(4.79)	5.80*	(3.23)	0.74
N	99490		99490			99490		99490		
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 A2: Heat stress and corporate bond spreads with Oster (2019) δ

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, and credit-rating fixed effects. Sample includes only non-investment grade bonds. Last 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. Oster (2019) δ is calculated under the assumption that R_{max}=1.

y-variable	Spread					OAS				
	coef	se	coef	se	δ	coef	se	coef	se	δ
Risk×I_{2007}	5.46	(5.15)	5.44	(3.75)	2.50	1.26	(9.11)	3.47	(7.41)	-0.54
Risk×I_{2008}	-73.46	(49.08)	-30.90	(19.19)	0.28	-36.77*	(21.52)	-24.78	(16.80)	0.40
Risk×I_{2009}	-79.76	(49.85)	-39.04	(25.24)	0.35	-0.70	(22.34)	1.50	(18.34)	-0.19
Risk×I_{2010}	37.07*	(19.73)	35.08**	(14.35)	1.85	3.07	(14.76)	6.21	(8.38)	-0.76
Risk×I_{2011}	48.60*	(25.17)	40.57**	(15.92)	1.19	1.19	(13.97)	3.80	(10.54)	-0.49
Risk×I_{2012}	51.84**	(24.10)	45.10***	(16.85)	1.37	0.06	(12.83)	2.61	(10.75)	-0.32
Risk×I_{2013}	48.90**	(23.55)	43.66***	(16.01)	1.59	15.75	(12.78)	25.02***	(9.38)	-1.19
Risk×I_{2014}	46.06*	(23.52)	44.03***	(15.89)	2.08	10.09	(11.99)	15.72*	(8.53)	-1.28
Risk×I_{2015}	52.93**	(24.48)	52.57***	(17.90)	2.78	15.37	(12.51)	19.74**	(9.50)	-8.11
Risk×I_{2016}	52.57**	(21.93)	51.94***	(16.35)	2.88	25.45**	(12.29)	32.62***	(9.03)	-7.11
Risk×I_{2017}	43.79**	(20.95)	40.76***	(15.10)	2.01	18.40	(12.33)	20.88**	(8.98)	3.48
Risk×I_{2018}	41.10**	(20.51)	33.78**	(14.90)	1.17	12.79	(13.12)	12.73	(10.33)	1.27
Risk×I_{2019}	42.85**	(20.30)	34.59**	(15.03)	1.24	9.63	(13.20)	10.24	(9.60)	2.93
Risk×I_{2020}	36.87*	(20.79)	32.99**	(15.85)	1.85	17.34	(15.23)	25.14*	(13.32)	-2.44
N	38606		38606			5602		5602		
R^2	0.72		0.81			0.82		0.86		
Firm & Time FE	Y		Y			Y		Y		
Controls	N		Y			N		Y		
Rating x Year FE	N		Y			N		Y		

Additional matched sample results

Table A3: Heat damage components 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 a risk measure 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. Panel A presents the average covariates for the two samples. Panel B presents estimation results for panel regressions where the difference in maturity-matched credit spreads between the matched bonds is regressed on year dummies. Standard errors are two-way clustered by treat county and month. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Risk	Energy damage		High-risk labor		Low-risk labor		Δ Proj Hot days	
I_{2007}	10.85	(7.54)	-12.90*	(6.81)	-12.73	(9.11)	-7.23	(8.29)
I_{2008}	10.48	(12.97)	7.66	(9.96)	16.25	(11.58)	12.40	(13.19)
I_{2009}	4.18	(15.26)	11.36	(16.71)	11.48	(18.46)	43.30**	(17.52)
I_{2010}	13.16	(9.94)	18.37**	(9.17)	-4.44	(9.86)	19.33*	(10.79)
I_{2011}	3.67	(11.13)	-3.56	(8.08)	10.70	(12.58)	0.38	(11.86)
I_{2012}	28.07***	(9.43)	12.24	(7.94)	18.60*	(11.14)	21.41**	(10.23)
I_{2013}	26.56***	(7.97)	14.38**	(6.56)	16.86	(10.73)	25.31***	(8.18)
I_{2014}	29.14***	(7.71)	16.96**	(7.26)	10.72	(11.17)	25.41***	(8.04)
I_{2015}	39.34***	(8.43)	29.21***	(7.17)	13.07	(11.44)	31.82***	(8.48)
I_{2016}	35.44***	(7.84)	20.96***	(7.40)	17.21	(11.33)	35.69***	(8.31)
I_{2017}	34.99***	(8.32)	23.59***	(6.95)	16.59	(10.75)	28.29***	(7.93)
I_{2018}	35.85***	(7.99)	25.85***	(6.94)	19.10*	(10.81)	34.52***	(8.00)
I_{2019}	36.58***	(7.96)	17.79**	(7.28)	14.52	(11.05)	31.57***	(8.07)
I_{2020}	29.95***	(11.08)	10.85	(9.77)	17.52	(12.07)	30.23***	(9.68)
N	19708		19696		19613		19674	
R^2	0.11		0.11		0.12		0.14	
County FE	Y							

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 (h) in Figure 3).

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 A4 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. (2022) 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. (2022) 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.

Table A4: All risk scores

The table presents estimation results for municipal bonds (from Table 3), non-investment grade corporate bonds (From Table 7 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	
$Risk \times 1_{2007}$	1.89	(2.16)	-2.22	(2.84)	-3.14	(2.07)	0.76	(1.79)	0.23	(1.09)
$Risk \times 1_{2008}$	2.15	(3.27)	-1.73	(3.64)	-3.01	(3.17)	6.87^{***}	(2.46)	-1.23	(1.63)
$Risk \times 1_{2009}$	2.51	(3.71)	9.59^{**}	(4.58)	7.25^{*}	(4.31)	6.00^{*}	(3.38)	-1.09	(2.18)
$Risk \times 1_{2010}$	0.73	(3.75)	6.61	(4.35)	-0.48	(4.08)	2.66	(3.00)	-3.26	(2.14)
$Risk \times 1_{2011}$	-0.79	(4.16)	7.99^{*}	(4.28)	4.45	(4.93)	1.00	(3.20)	-1.68	(2.46)
$Risk \times 1_{2012}$	5.20	(3.83)	5.62	(3.95)	0.22	(3.96)	1.22	(3.30)	-1.40	(2.16)
$Risk \times 1_{2013}$	6.57^{*}	(3.53)	3.11	(3.75)	0.50	(3.80)	1.14	(2.92)	-2.19	(1.96)
$Risk \times 1_{2014}$	7.34^{**}	(3.52)	2.69	(3.83)	1.61	(3.75)	0.23	(2.92)	-1.38	(2.01)
$Risk \times 1_{2015}$	8.63^{**}	(3.58)	4.00	(3.83)	1.70	(3.69)	0.69	(2.94)	-1.12	(2.07)
$Risk \times 1_{2016}$	9.22^{***}	(3.53)	3.50	(3.73)	-0.38	(3.57)	2.05	(2.85)	-1.92	(1.98)
$Risk \times 1_{2017}$	8.11^{**}	(3.47)	3.98	(3.71)	-0.26	(3.56)	2.32	(2.82)	-2.36	(1.94)
$Risk \times 1_{2018}$	8.62^{**}	(3.53)	2.63	(3.74)	-0.54	(3.64)	3.42	(2.85)	-2.57	(1.96)
$Risk \times 1_{2019}$	8.08^{**}	(3.55)	2.23	(3.72)	-0.25	(3.65)	1.02	(2.86)	-1.86	(1.99)
$Risk \times 1_{2020}$	6.92^{*}	(3.64)	2.42	(3.80)	-1.39	(3.77)	1.49	(2.96)	-0.30	(2.03)
N	99344									
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$\times I_{2007}$	9.85	(6.81)	7.45**	(3.47)	-8.49**	(4.28)	-8.23	(6.78)	14.52**	(6.59)
Risk$\times I_{2008}$	2.45	(25.42)	-12.12	(12.66)	-31.11**	(15.34)	-0.16	(25.60)	26.82	(26.16)
Risk$\times I_{2009}$	-54.25*	(29.76)	37.34*	(20.58)	8.28	(19.51)	78.28**	(36.35)	65.76***	(21.11)
Risk$\times I_{2010}$	23.56	(17.09)	36.87**	(15.74)	-3.33	(14.12)	0.31	(21.34)	35.87***	(11.45)
Risk$\times I_{2011}$	27.24	(18.40)	32.49*	(18.12)	-0.45	(15.30)	-15.48	(21.72)	30.18**	(13.08)
Risk$\times I_{2012}$	20.00	(17.78)	35.43	(22.12)	15.28	(15.43)	0.51	(24.76)	16.53	(13.04)
Risk$\times I_{2013}$	33.80*	(17.66)	19.09	(18.53)	3.54	(14.56)	-18.88	(25.43)	18.96	(11.75)
Risk$\times I_{2014}$	36.16**	(18.11)	21.65	(16.43)	2.62	(14.29)	-25.21	(26.23)	16.31	(11.34)
Risk$\times I_{2015}$	41.13**	(18.74)	22.03	(16.93)	10.80	(15.46)	-36.33	(26.46)	4.39	(13.12)
Risk$\times I_{2016}$	41.79**	(18.91)	25.76	(16.03)	12.92	(16.55)	-24.47	(25.19)	-6.84	(15.10)
Risk$\times I_{2017}$	35.52**	(17.70)	18.90	(16.32)	9.60	(16.10)	-17.78	(24.30)	-2.14	(13.17)
Risk$\times I_{2018}$	31.82*	(17.73)	15.90	(16.59)	5.94	(15.54)	-19.54	(24.55)	2.41	(13.82)
Risk$\times I_{2019}$	31.06*	(17.29)	18.90	(16.41)	8.62	(14.81)	-25.52	(24.94)	5.87	(14.38)
Risk$\times I_{2020}$	44.84**	(19.42)	0.77	(16.46)	10.82	(15.54)	-52.58*	(27.22)	15.37	(17.88)
N	38606									
R^2	0.83									
Firm & Time FE		Y								
Controls		Y								
Rating x Year FE		Y								

Panel C: Equities										
Risk	Heat score		Water score		Flood score		Hurricane score		Sealevel score	
Risk$\times I_{2007}$	22.52**	(11.16)	-24.97***	(8.59)	-7.98	(5.58)	0.87	(5.97)	18.58**	(7.87)
Risk$\times I_{2008}$	14.17	(31.74)	5.60	(28.31)	-68.08**	(26.52)	11.02	(24.67)	56.83*	(28.87)
Risk$\times I_{2009}$	-6.74	(30.49)	-9.96	(25.93)	-57.90*	(29.72)	43.02	(34.07)	20.97	(25.22)
Risk$\times I_{2010}$	2.06	(11.01)	-12.34	(9.60)	-2.60	(7.88)	2.79	(8.45)	6.19	(9.18)
Risk$\times I_{2011}$	-0.85	(12.65)	5.13	(10.19)	-0.54	(8.45)	10.18	(10.11)	-3.05	(8.32)
Risk$\times I_{2012}$	25.69**	(12.61)	-14.28	(10.96)	1.72	(7.69)	-2.28	(8.93)	0.54	(9.69)
Risk$\times I_{2013}$	33.73***	(12.49)	-17.28	(11.48)	-1.05	(7.57)	-9.77	(8.67)	7.34	(10.71)
Risk$\times I_{2014}$	30.45**	(14.56)	4.41	(11.55)	9.03	(7.45)	8.48	(8.98)	-14.33	(11.16)
Risk$\times I_{2015}$	35.99**	(14.67)	-3.75	(12.50)	14.19*	(7.62)	2.71	(10.04)	-8.90	(11.61)
Risk$\times I_{2016}$	46.05***	(14.67)	-6.35	(12.96)	28.14***	(8.04)	-12.24	(10.56)	-8.89	(11.16)
Risk$\times I_{2017}$	39.26**	(16.28)	-25.42*	(13.13)	19.96**	(8.48)	-9.90	(10.96)	-13.44	(13.10)
Risk$\times I_{2018}$	39.24***	(14.92)	-22.46	(14.12)	15.69*	(9.07)	-19.66*	(10.88)	-13.79	(12.96)
Risk$\times I_{2019}$	50.34***	(17.52)	-22.92	(15.36)	11.60	(10.53)	-5.20	(12.32)	-23.81	(14.72)
Risk$\times I_{2020}$	61.85**	(29.61)	-16.12	(27.80)	15.62	(24.86)	-23.25	(21.35)	-3.81	(25.62)
N	74899									
R^2	0.70									
Firm & Time FE		Y								
Controls		Y								

Appendix B: 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[37]). 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.

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 sub-

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

division 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[38] 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 ('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))

[38]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.

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.[39] 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.)

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.)

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

5. If CUSIP name is still matched to both counties and places, remove places if countywords 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.