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

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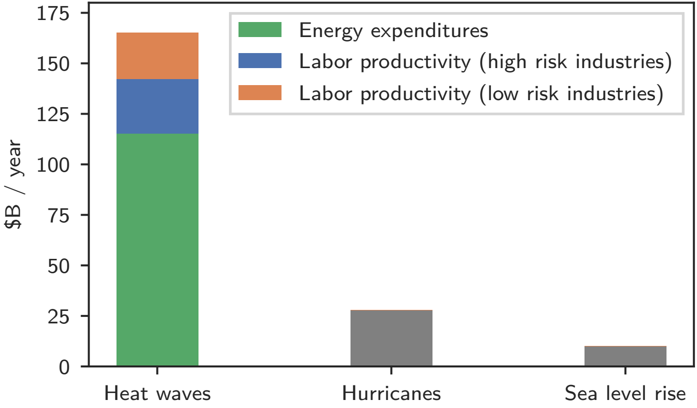
Heat waves are likely to cause large economic damages

Figure: Estimated climate change damages in the U.S.



Source: Hsiang et al. (2017) and own calculations, Hallegate et al. (2013)

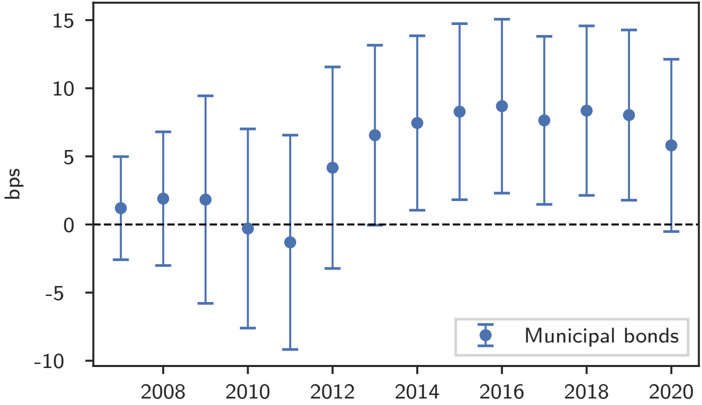
Example 1
Example 2
Example 3
Alternative estimates

Is physical risk priced?

1. Heat stress increases municipal and corporate bond spreads, and conditional expected returns on equities
   - Muni bonds: 15bps for damages that equal to 1% of GDP
   - Corporate bonds: 40bps for one standard deviation of heat exposure
   - Equities: Heat stress *increases* conditional expected returns on stocks 45bps for one standard deviation of heat exposure
2. Heat stress increases physical default probablilities on corporate bonds, as proxied by Expected Default Frequency (EDF)
3. We don't find similar results for alternative physical risks
   - Unlike many other climate hazards heat stress affects large geographical areas simultaneously, making it less diversifiable. Also insurance markets for heat stress are virtually nonexistent.

Main results

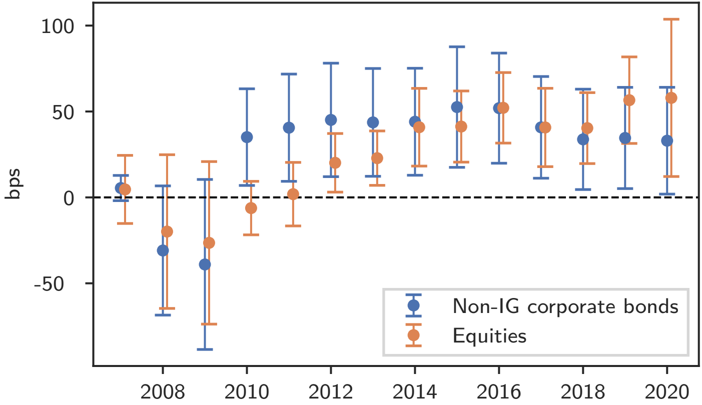
Figure: Estimated impact of heat score on spreads



Google trends

Main results

Figure: Estimated impact of heat score on spreads and expected returns



Google trends

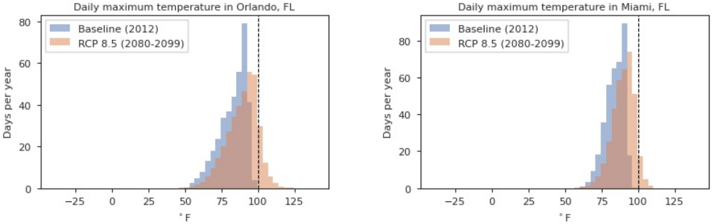
Heat stress measure 1: SEAGLAS

- Hsiang et al. (Science 2017) develop 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 perils using data up to 2013.
- Compares projected annual economic damages under RCP8.5 climate scenario to a counterfactual scenario with no further climate change during the last two decades of the 21st century

RCP
Limitations

Heat stress measure 1: SEAGLAS

- Step 1: Construct probabilistic projections of daily temperatures using 44 existing climate change models from Rasmussen et al. (2016)



- We define Δ Proj Hot days as projected change in the number of hot days per year between RCP 8.5 and Baseline scenarios
  - Orlando is in 76th and Miami in 24th percentile

SD-Phoenix

SF-Sacramento

Heat stress measure 1: SEAGLAS

- Step 2: Use temperature distributions to predict economic damages using hazard-specific dose-response functions
  - Energy demand: U.S. Energy Information Administration's National Energy Modeling System (NEMS)
  - Labor productivity: Graff Zivin and Neidell (2014)
- Difference between RCP 8.5 and Baseline provides scale-free measure of changes in energy consumption and labor supply
- Example: Energy expenditures in Orlando increase by 13.8%, labor productivity decreases by 2.5% in high-risk industries and by 0.5% in low-risk industries
- Step 3: Convert intensive measures into dollar damages (as a fraction of GDP) using 2019 state-level data on energy expenditures and wages by industry.

Heat stress measure 2: Four Twenty Seven, Inc.

- County-level exposure scores (0-100) for various perils
  - **Heat stress**, Drought, Excess rainfall, Hurricanes, Sea level
- Companies mapped to geographical areas based on physical asset locations (e.g. offices and production plants)
- Limitations: proprietary and relative measure, single snapshot from 2019

Summary statistics for risk measures

Variable	*N*	Mean	Std	Min	25%	Median	75%	Max
Heat damage	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

Hot days is the average number of hot days in a year between 2011 and 2020. Δ Hot days is the change in the average number of hot days between 2001-2010 and 2011-2020.

- For average municipality, annual heat-related damages are 0.83% of GDP
- For median municipality, the number of hot days per year is projected to increase by 37 days from the current level of 0.4

Correlations

Identification

Challenge: heat exposure has few discontinuities in the cross-section

Figure: Heat score (0.978)

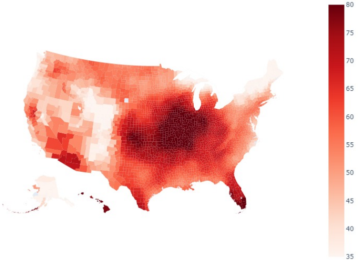
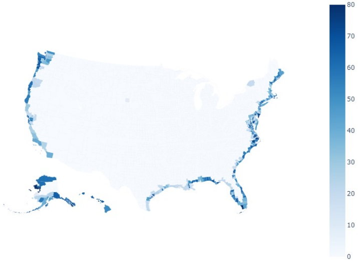


Figure: Sea level score (0.283)



Rank correlation of risk scores among pairs of adjacent counties is shown in parentheses

Number of Observations

Identification (Cont'd)

Observation: historically, credit ratings didn't reflect climate risks

> *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" (2015)

- In its 2021 ESG risk framework, S&P requires that it has "sufficient visibility and certainty" on an ESG factor to include it in the credit rating analysis. Physical climate risks generally don't meet these criteria.

Identification (Cont'd)

Observation: historically, credit ratings didn't reflect climate risks

- Adding flexible credit rating fixed effects (year $\times$ rating) control for "traditional" credit risks does not introduce a "bad control problem"
- In principle, this allows us to directly control for any confounding credit risk factors
- In practice, credit ratings are imperfect proxies for credit risk
- We use Oster (2019) methodology to assess the maximal impact of hypothetical omitted credit risk factors on coefficient estimates

Muni Bonds: Empirical Specification

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

- $Spread_{b,c,t}$ is the difference between secondary market yield and maturity-matched benchmark rate
- Coefficient of interest α_y estimates yearly sensitivity of credit spreads to heat stress (compared to 2006)
- Yearly coefficients in Z control for 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, state-level energy expenditures per capita, and **credit-rating fixed effects**
- Standard errors double clustered by year-month and county

Data

Heat stress and municipal bond spreads

Risk	Heat damage (% GDP)				Heat score			
Risk $\times I_{2007}$	-1.60	(5.79)	-1.70	(5.41)	2.54	(2.45)	1.20	(1.93)
Risk $\times I_{2008}$	13.54	(9.72)	8.39	(8.23)	-0.16	(5.49)	1.90	(2.50)
Risk $\times I_{2009}$	34.08**	(16.16)	21.10**	(10.42)	-1.62	(7.33)	1.83	(3.89)
Risk $\times I_{2010}$	10.87	(9.99)	6.98	(9.43)	-0.37	(5.32)	-0.29	(3.73)
Risk $\times I_{2011}$	3.76	(10.37)	9.11	(9.34)	1.57	(5.29)	-1.31	(4.01)
Risk $\times I_{2012}$	9.23	(9.55)	17.17**	(8.12)	4.50	(4.97)	4.17	(3.77)
Risk $\times I_{2013}$	16.41*	(9.20)	17.69**	(7.61)	8.15*	(4.68)	6.55*	(3.37)
Risk $\times I_{2014}$	17.49*	(9.16)	16.04**	(7.62)	9.71**	(4.67)	7.45**	(3.27)
Risk $\times I_{2015}$	20.71**	(9.49)	19.65**	(7.59)	10.73**	(4.62)	8.28**	(3.30)
Risk $\times I_{2016}$	21.84**	(9.67)	21.26***	(7.43)	10.57**	(4.67)	8.68***	(3.26)
Risk $\times I_{2017}$	21.02**	(9.37)	20.23***	(7.31)	9.39**	(4.65)	7.64**	(3.15)
Risk $\times I_{2018}$	20.34**	(9.45)	20.58***	(7.58)	9.86**	(4.68)	8.35***	(3.17)
Risk $\times I_{2019}$	19.64**	(9.72)	19.01**	(7.41)	9.77**	(4.70)	8.03**	(3.19)
Risk $\times I_{2020}$	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	

Average Oster (2019) δ is 2.7 and 1.8 for the two measures.

Matching

Muni Bonds: Subsamples and mechanism

Result is mainly coming from:

- Bonds with low credit rating (AA- or lower)
- Long-term bonds (10+ years)
- Revenue bonds

We can decompose heat damage exposure to its components:

- Energy expenditure
- High-risk labor
- Low-risk labor
- Raw temperature projection

Rating
Maturity
Bond Type
Decomposition

Heat score and corporate bond spreads

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

Data

Specification

From spreads to expected returns

- Evidence about credit spreads does not distinguish between expected loss and risk-premium
  - Credit spread $\approx$ Expected loss $\times$ Risk-premium
- To make further progress, we'll turn to equities
  - Likely to be more sensitive to cash flow shocks than debt

Measuring conditional expected returns

- Problem: due to the time-varying nature of climate risk (e.g. Pastor et al., 2021), we need a measure for *conditional* expected returns

- Martin (2017) and Martin and Wagner (2019) propose measures for conditional expected return that are related to the risk-neutral variance of the underlying asset

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

$$SVIX^2_t = \frac{2}{R_{f,t+1}S^2_{m,t}} \left[\int_0^{F_{m,t}} \text{put}_{m,t}(K)dK + \int_{F_{m,t}}^{\infty} \text{call}_{m,t}(K)dK \right]$$

More

MW Fig 6

Heat score and conditional expected returns on equity

y-variable	$E_t(R_{t+1})$				$E_t(R_{t+1})(1-L_t)$	
Heat score $\times I_{2007}$	0.53	(7.22)	4.64	(10.11)	-3.12	(8.08)
Heat score $\times I_{2008}$	-18.84	(21.93)	-19.89	(22.82)	-37.24*	(21.67)
Heat score $\times I_{2009}$	-18.00	(25.98)	-26.46	(24.13)	-46.42***	(16.51)
Heat score $\times I_{2010}$	6.55	(9.35)	-6.22	(7.95)	-15.33**	(7.58)
Heat score $\times I_{2011}$	1.04	(10.33)	1.88	(9.43)	-15.73*	(8.53)
Heat score $\times I_{2012}$	12.01	(9.13)	20.13**	(8.70)	9.51	(7.31)
Heat score $\times I_{2013}$	23.44**	(9.05)	22.84***	(8.08)	16.43**	(6.95)
Heat score $\times I_{2014}$	18.78*	(10.80)	40.85***	(11.54)	28.95***	(9.07)
Heat score $\times I_{2015}$	46.09***	(11.38)	41.23***	(10.57)	30.84***	(8.19)
Heat score $\times I_{2016}$	43.13***	(12.89)	52.14***	(10.47)	38.00***	(8.26)
Heat score $\times I_{2017}$	27.51**	(12.56)	40.70***	(11.63)	32.29***	(9.02)
Heat score $\times I_{2018}$	20.95*	(11.79)	40.33***	(10.53)	30.09***	(8.08)
Heat score $\times I_{2019}$	25.47*	(13.05)	56.59***	(12.85)	42.17***	(9.65)
Heat score $\times I_{2020}$	88.00***	(28.22)	57.93**	(23.35)	23.06	(16.57)
N	77214		74899		74633	
R^2	0.66		0.70		0.70	
Firm & Time FE	Y		Y		Y	
Controls	N		Y		Y	

Data

Specification

Other physical risks

- In addition to heat stress, we can also measure various other physical climate risks
  - Droughts, Excess rainfall, Floods, Hurricanes, Sea level rise
- Caveat: any within-municipality variation in risk exposure biases our results towards zero
  - Relevant especially for sea level risk and to a lesser extent hurricane risk

Muni Bonds: Results

Panel A: Municipal Bonds										
Risk	Heat score		Water score		Rainfall score		Hurricane score		Sealevel score	
Risk × 1_{2007}	1.89	(2.16)	-2.22	(2.84)	-3.14	(2.07)	0.76	(1.79)	0.23	(1.09)
Risk × 1_{2008}	2.15	(3.27)	-1.73	(3.64)	-3.01	(3.17)	6.87***	(2.46)	-1.23	(1.63)
Risk × 1_{2009}	2.51	(3.71)	9.59**	(4.58)	7.25*	(4.31)	6.00*	(3.38)	-1.09	(2.18)
Risk × 1_{2010}	0.73	(3.75)	6.61	(4.35)	-0.48	(4.08)	2.66	(3.00)	-3.26	(2.14)
Risk × 1_{2011}	-0.79	(4.16)	7.99*	(4.28)	4.45	(4.93)	1.00	(3.20)	-1.68	(2.46)
Risk × 1_{2012}	5.20	(3.83)	5.62	(3.95)	0.22	(3.96)	1.22	(3.30)	-1.40	(2.16)
Risk × 1_{2013}	6.57*	(3.53)	3.11	(3.75)	0.50	(3.80)	1.14	(2.92)	-2.19	(1.96)
Risk × 1_{2014}	7.34**	(3.52)	2.69	(3.83)	1.61	(3.75)	0.23	(2.92)	-1.38	(2.01)
Risk × 1_{2015}	8.63**	(3.58)	4.00	(3.83)	1.70	(3.69)	0.69	(2.94)	-1.12	(2.07)
Risk × 1_{2016}	9.22***	(3.53)	3.50	(3.73)	-0.38	(3.57)	2.05	(2.85)	-1.92	(1.98)
Risk × 1_{2017}	8.11**	(3.47)	3.98	(3.71)	-0.26	(3.56)	2.32	(2.82)	-2.36	(1.94)
Risk × 1_{2018}	8.62**	(3.53)	2.63	(3.74)	-0.54	(3.64)	3.42	(2.85)	-2.57	(1.96)
Risk × 1_{2019}	8.08**	(3.55)	2.23	(3.72)	-0.25	(3.65)	1.02	(2.86)	-1.86	(1.99)
Risk × 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									

High-yield Corporate Bonds: Results

Panel B: Corporate Bonds										
Risk	Heat score		Water score		Flood score		Hurricane score		Sealevel score	
Risk × I_{2007}	9.85	(6.81)	7.45**	(3.47)	-8.49**	(4.28)	-8.23	(6.78)	14.52**	(6.59)
Risk × I_{2008}	2.45	(25.42)	-12.12	(12.66)	-31.11**	(15.34)	-0.16	(25.60)	26.82	(26.16)
Risk × I_{2009}	-54.25*	(29.76)	37.34*	(20.58)	8.28	(19.51)	78.28**	(36.35)	65.76***	(21.11)
Risk × I_{2010}	23.56	(17.09)	36.87**	(15.74)	-3.33	(14.12)	0.31	(21.34)	35.87***	(11.45)
Risk × I_{2011}	27.24	(18.40)	32.49*	(18.12)	-0.45	(15.30)	-15.48	(21.72)	30.18**	(13.08)
Risk × I_{2012}	20.00	(17.78)	35.43	(22.12)	15.28	(15.43)	0.51	(24.76)	16.53	(13.04)
Risk × I_{2013}	33.80*	(17.66)	19.09	(18.53)	3.54	(14.56)	-18.88	(25.43)	18.96	(11.75)
Risk × I_{2014}	36.16**	(18.11)	21.65	(16.43)	2.62	(14.29)	-25.21	(26.23)	16.31	(11.34)
Risk × I_{2015}	41.13**	(18.74)	22.03	(16.93)	10.80	(15.46)	-36.33	(26.46)	4.39	(13.12)
Risk × I_{2016}	41.79**	(18.91)	25.76	(16.03)	12.92	(16.55)	-24.47	(25.19)	-6.84	(15.10)
Risk × I_{2017}	35.52**	(17.70)	18.90	(16.32)	9.60	(16.10)	-17.78	(24.30)	-2.14	(13.17)
Risk × I_{2018}	31.82*	(17.73)	15.90	(16.59)	5.94	(15.54)	-19.54	(24.55)	2.41	(13.82)
Risk × I_{2019}	31.06*	(17.29)	18.90	(16.41)	8.62	(14.81)	-25.52	(24.94)	5.87	(14.38)
Risk × 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									

Equities: Results

Panel C: Equities

Risk score	Heat		Water		Flood		Hurricane		Sealevel	
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									

Conclusion

- Heat stress seems to be a systematically priced source of risk across different asset classes
  - Positive premium suggests climate change having significant negative impact on aggregate economy
  - Implications for discount rates used for climate abatement investments
- How risk exposure is measured is important
  - Implications for the ongoing policy debate on climate risk disclosure requirements

Thank you for your attention !

Related literature

1. Carbon/transition risk
   - Bolton and Kacperczyk (2021a, 2021b), Ilhan et al. (2020), Seltzer et al. (2020), Sautner et al. (2021)
2. Physical risk
   - Painter (2020), Goldsmith-Pinkham et al. (2021), Bernstein et al. (2019), Baldauf et al., (2020), Giglio et al., (2021), Murfin and Spiegel (2020), Bansal et al. (2021), Correa et al. (2021)
3. Hedging climate risk
   - Engle et al. (2020), Alekseev et al. (2021)

Outline

Appendix

Heat waves are likely to cause large economic damages

California debates naming heatwaves to underscore deadly risk of extreme heat

Climate scientists from around the world issued dire warnings on Monday, in the latest IPCC report on the dangers posed in the unfolding climate crisis. Among them is extreme heat, a crisis that on average already claims more American lives than hurricanes and tornadoes combined.

Source: The Guardian, Mar 1 2022

Back

Heat waves are likely to cause large economic damages

Moody's warns nuclear plants face growing climate risk

Nuclear operators should expect to face growing credit risk associated with climate change over the next 10 to 20 years, Moody's said in an Aug. 18 [2020] report – – Some 48,000 MW of nuclear capacity will be impacted by the increased exposure to combined rising heat and water stress, according to the report.*

* 48% of total nuclear power capacity in the U.S., 4% of total capacity

Source: S&P Global Market Intelligence, Aug 19 2020

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Heat waves are likely to cause large economic damages

Paradise, the Wildfire-Ravaged California Town, Warns of Municipal Bond Default

PG&E: The First Climate-Change Bankruptcy, Probably Not the Last

The fast fall of PG&E after California's wildfires is a jolt for companies considering the uncertain risks of a warming planet

Oregon establishes rules to protect outdoor workers from heat, wildfire smoke

Sources: The Wall Street Journal, January 18, 2019 & July 22, 2022, Statesman Journal May 11, 2022

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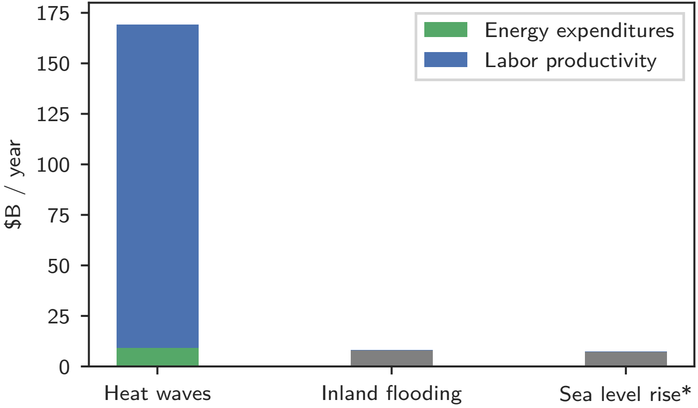
Heat waves are likely to cause large economic damages

Figure: Estimated climate change damages in the U.S.



Source: Fourth National Climate Assessment (2017), * with adaptation

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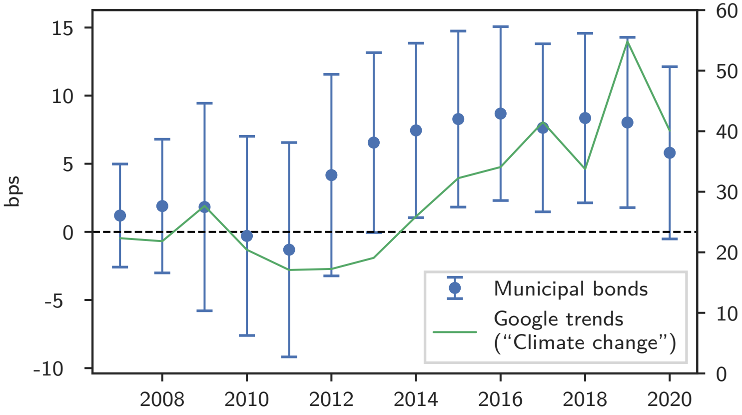
Main results with Google Trends

Figure: Estimated impact of heat score on spreads



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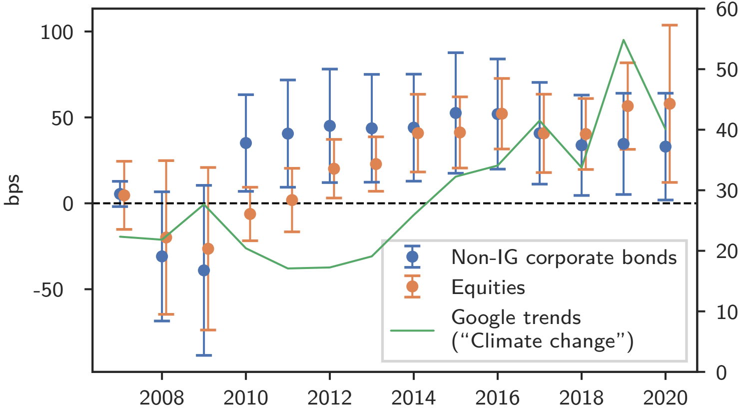
Main results with Google Trends

Figure: Estimated impact of heat score on spreads and expected returns



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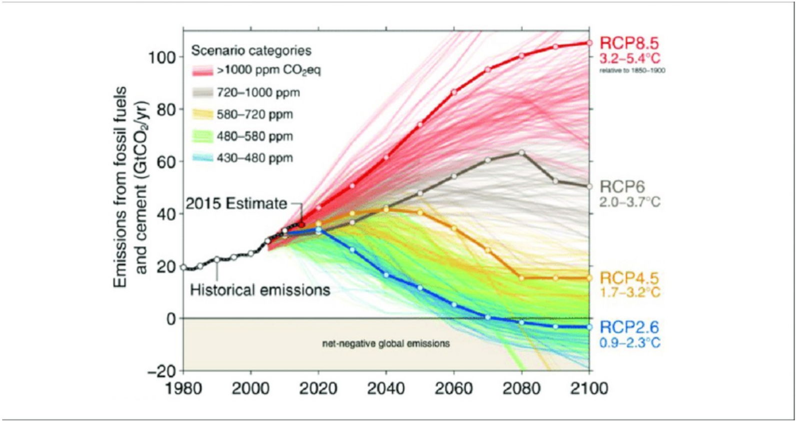
Representative Concentration Pathway (RCP)



Source: Neil Craik (University of Waterloo)

- Example: 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

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Heat stress measure 1: Hsiang et al. (Science 2017)

Limitations:

- Excludes various channels
  - E.g. damages to infrastructure and human health
- Assumes the structure of U.S. economy stays constant
  - Energy prices stay constant and supply is fully elastic
  - No migration

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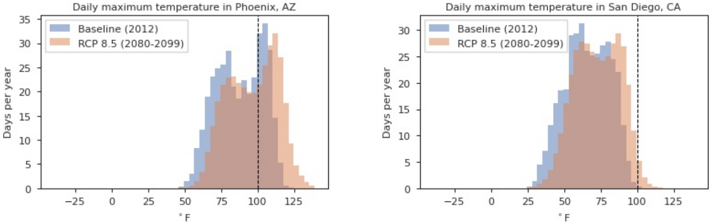
Heat stress measure 1: SEAGLAS

- Step 1: Construct probabilistic projections of daily temperatures using 44 existing climate change models from Rasmussen et al. (2016)



- We define Δ Proj Hot days as projected change in the number of hot days per year between RCP 8.5 and Baseline scenarios
  - Phoenix is in 81st and San Diego in 5th percentile

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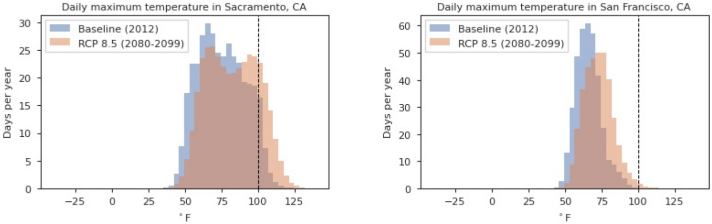
Heat stress measure 1: SEAGLAS

- Step 1: Construct probabilistic projections of daily temperatures using 44 existing climate change models from Rasmussen et al. (2016)



- We define Δ Proj Hot days as projected change in the number of hot days per year between RCP 8.5 and Baseline scenarios
  - Sacramento is in 63rd and San Francisco in 1st percentile

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Data: Heat stress exposure of U.S. municipalities

	Heat damage	Energy damage	High-risk labor	Low-risk labor	Heat score	Δ Proj Hot days	Δ Hot days	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

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Identification

Challenge: heat exposure has few discontinuities in the cross-section

Figure: Heat score (9)

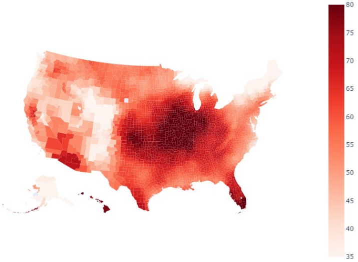
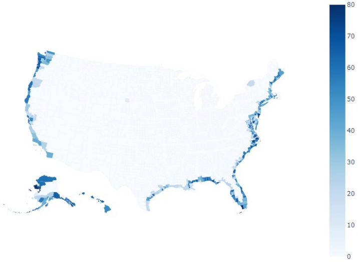


Figure: Sea level score (587)



Number of adjacent county pairs with risk score difference $\geq$20 is shown in parentheses

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Muni Bonds: Data

- Sources:
  - Characteristics and ratings: Mergent Municipal Bonds
  - Secondary market prices: MSRB EMMA
- Matched to Census geolocations by issuer name and state
- Sample selection:
  - Fixed coupon
  - Uninsured
  - Tax-exempt
  - More than 3 months since issuance, at least 1 year to maturity
  - Not state-issued
  - Positive spread
  - Trim right tail at 2.5% level
  - 2006-2020

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Summary statistics for municipal bonds

Variable	N	Mean	Std	Min	25%	Median	75%	Max
Spread (bps)	99490	68.75	59.50	0.00	32.11	54.91	83.62	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
Heat score	99490	60.43	11.28	0.00	53.14	58.51	68.50	90.61

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Matched sample 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

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Heat stress and municipal bond spreads (matched sample)

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	

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Heat damage and municipal bond spreads by credit rating

Sample	High rating		Low rating	
Heat dmg $\times I_{2007}$	3.30	(5.37)	-10.72	(12.70)
Heat dmg $\times I_{2008}$	0.89	(9.15)	21.69	(16.05)
Heat dmg $\times I_{2009}$	5.46	(10.91)	39.45**	(18.08)
Heat dmg $\times I_{2010}$	-1.77	(10.12)	18.00	(17.91)
Heat dmg $\times I_{2011}$	2.21	(9.23)	10.84	(17.76)
Heat dmg $\times I_{2012}$	11.81	(9.78)	16.51	(16.81)
Heat dmg $\times I_{2013}$	10.76	(9.65)	18.61	(15.47)
Heat dmg $\times I_{2014}$	8.97	(9.74)	19.87	(15.59)
Heat dmg $\times I_{2015}$	10.98	(9.91)	28.68*	(15.30)
Heat dmg $\times I_{2016}$	11.96	(9.96)	33.44**	(15.83)
Heat dmg $\times I_{2017}$	12.10	(9.76)	26.45*	(15.12)
Heat dmg $\times I_{2018}$	11.88	(10.02)	30.68*	(15.72)
Heat dmg $\times I_{2019}$	9.91	(9.87)	31.33**	(14.83)
Heat dmg $\times I_{2020}$	9.27	(10.13)	17.87	(14.25)
N	70464		29026	
R^2	0.34		0.67	
County & Time FE	Y			
Controls	Y			
Rating x Year FE	Y			

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Heat damage and municipal bond spreads by maturity

Sample	Short-term		Long-term	
Heat dmg × I_{2007}	-8.63	(9.59)	10.48	(6.65)
Heat dmg × I_{2008}	-12.53	(11.78)	25.43**	(11.17)
Heat dmg × I_{2009}	-2.72	(12.98)	38.71***	(12.84)
Heat dmg × I_{2010}	-15.72	(13.41)	25.47**	(10.52)
Heat dmg × I_{2011}	-6.03	(11.66)	25.03**	(12.22)
Heat dmg × I_{2012}	3.47	(11.37)	31.54***	(9.28)
Heat dmg × I_{2013}	2.75	(10.04)	31.62***	(8.97)
Heat dmg × I_{2014}	1.54	(10.53)	29.18***	(8.59)
Heat dmg × I_{2015}	-1.79	(10.51)	37.13***	(8.31)
Heat dmg × I_{2016}	1.74	(10.48)	37.63***	(8.63)
Heat dmg × I_{2017}	0.26	(10.47)	37.65***	(8.23)
Heat dmg × I_{2018}	6.01	(10.25)	34.99***	(8.68)
Heat dmg × I_{2019}	2.48	(10.28)	33.51***	(8.46)
Heat dmg × I_{2020}	2.09	(10.39)	30.71***	(8.65)
N	43289		56201	
R^2	0.65		0.62	
County & Time FE	Y			
Controls	Y			
Rating x Year FE	Y			

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Heat damage and municipal bond spreads by bond type

Sample	GO		Revenue	
Heat dmg × I_{2007}	4.80	(7.46)	0.99	(8.58)
Heat dmg × I_{2008}	1.00	(7.36)	18.26	(12.71)
Heat dmg × I_{2009}	-2.00	(8.65)	37.66**	(14.54)
Heat dmg × I_{2010}	-9.72	(6.96)	19.10	(14.43)
Heat dmg × I_{2011}	-17.86**	(7.12)	22.98	(14.80)
Heat dmg × I_{2012}	-0.15	(6.22)	24.34*	(13.35)
Heat dmg × I_{2013}	-7.61	(6.13)	28.84**	(11.65)
Heat dmg × I_{2014}	-10.10	(6.16)	30.04**	(11.80)
Heat dmg × I_{2015}	-5.42	(6.11)	31.61***	(11.36)
Heat dmg × I_{2016}	-2.85	(5.94)	32.56***	(11.57)
Heat dmg × I_{2017}	-6.43	(6.19)	34.45***	(10.88)
Heat dmg × I_{2018}	-8.45	(6.05)	39.44***	(11.49)
Heat dmg × I_{2019}	-6.33	(5.97)	33.34***	(11.20)
Heat dmg × I_{2020}	-6.45	(6.41)	26.51**	(11.81)
N	43186		53287	
R^2	0.43		0.64	
County & Time FE	Y			
Controls	Y			
Rating x Year FE	Y			

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Heat damage components and municipal bond spreads

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							

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Corporate Bonds: Data

- Sources:
  - Characteristics and ratings: Mergent FISD (via WRDS Bond Returns)
  - Secondary market prices: TRACE (via WRDS Bond Returns)
  - Option-adjusted spreads (OAS): Morgan Stanley Research (Independent sample)
- Sample selection:
  - USD denominated
  - Non-144A
  - Nonconvertible
  - Senior unsecured
  - More than $100,000 offering amount
  - More than 3 months since issuance, at least 1 year to maturity
  - Positive spread
  - Trim right tail at 2.5% level
  - 2006-2020

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Summary statistics for corporate bonds

Variable	N	Mean	Std	Min	25%	Median	75%	Max
Spread (bps)	543004	156.79	140.29	0.00	78.23	122.40	190.69	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

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Corporate Bonds: Empirical Specification

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

- $Spread_{b,i,t}$ is the difference between secondary market yield and maturity-matched benchmark rate
- Coefficient of interest α_y estimates yearly sensitivity of credit spreads to heat score (compared to 2006)
- Yearly coefficients in Z control for 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**
- Standard errors double clustered by year-month and firm

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Expected Default Frequency: Empirical Specification

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

- $EDF_{i,t}$ is Expected Default Frequency by Moody's KMV
- Reflects a mapping from a Merton-model implied distance-to-default into a physical or statistical probability of default for the firm
- We use EDF to measure the cash flow risk to the corporate bond

Heat score and expected default frequency (EDF)

Sample	High rating		Low rating	
y-variable	EDF10		EDF10	
Heat score $\times I_{2007}$	-0.27	(0.65)	9.85^{*}	(5.43)
Heat score $\times I_{2008}$	-0.09	(1.24)	14.03^{**}	(6.76)
Heat score $\times I_{2009}$	1.95	(1.40)	21.71^{***}	(8.08)
Heat score $\times I_{2010}$	2.48^{**}	(1.20)	25.08^{***}	(8.72)
Heat score $\times I_{2011}$	0.47	(1.25)	29.95^{***}	(8.44)
Heat score $\times I_{2012}$	0.08	(1.24)	30.15^{***}	(8.06)
Heat score $\times I_{2013}$	0.61	(1.21)	35.31^{***}	(9.08)
Heat score $\times I_{2014}$	1.09	(1.30)	31.61^{***}	(9.38)
Heat score $\times I_{2015}$	4.22^{***}	(1.29)	36.59^{***}	(9.63)
Heat score $\times I_{2016}$	5.78^{***}	(1.39)	42.73^{***}	(11.36)
Heat score $\times I_{2017}$	6.33^{***}	(1.63)	49.29^{***}	(12.19)
Heat score $\times I_{2018}$	6.28^{***}	(1.61)	41.83^{***}	(11.85)
Heat score $\times I_{2019}$	6.26^{***}	(1.55)	31.29^{***}	(11.76)
Heat score $\times I_{2020}$	7.05^{***}	(1.87)	39.90^{***}	(10.64)
N	46235		7146	
R^2	0.90		0.79	
Firm & Time FE	Y			
Rating x Year FE	Y			

EDF Term-structure

What is the risk premium on heat stress exposure?

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

$$+ \beta EDF_{i,t} + \theta X_{b,i,t} + \varepsilon_{b,i,t}$$

- β_y's capture impact of average source of default risk on spreads both through its impact on expected losses and (multiplicative) risk premium
- α_y's capture whether heat stress related cash flow and risk premium effects are different than the average source of default risk

Heat score, EDF, and corporate bond spreads

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							

Heat score and expected default frequency (EDF)

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

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More on Martin-Wagner measure

- The measure is essentially the risk-neutral implied variance. In the cross-section, this should be driven by systematic risk differences (covariances with the SDF) – and hence proportional to stocks' expected return – provided that differences in idiosyncratic variances are stable.
- Knox and Vissing-Jørgensen (2022) show that Martin-Wagner measure is highly correlated with analysts' return expectations
- Applications: Lee et al. (2021), Pagano et al. (2021), Kim (2022)

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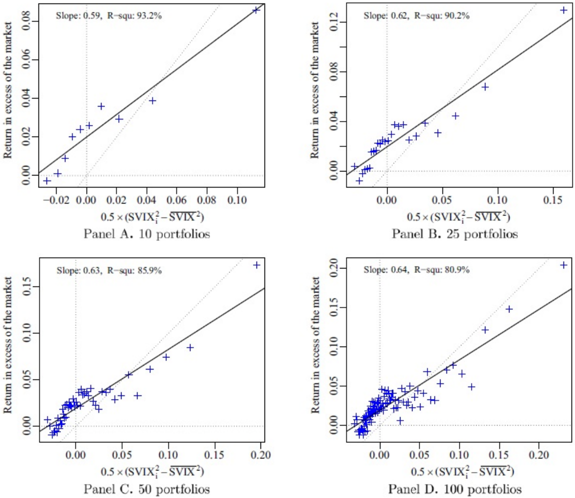
Portfolios sorted by stock risk-neutral variance



Source: Martin and Wagner (2019) Figure 6

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Equities: Data

- Sources:
  - Option prices and characteristics: OptionMetrics
  - Stock price and balance sheet items: CRSP-Compustat
- Sample:
  - S&P500 constituent in 2019
  - Positive expected excess return
  - Trim right tail at 2.5% level
  - 2006-2020

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Summary statistics for equities

Variable	N	Mean	Std	Min	25%	Median	75%	Max
$E_t(R^e_{t+1})$ (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

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Equities: Empirical Specification

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

- Coefficient of interest α_y estimates yearly sensitivity of expected returns to heat stress (compared to 2006)
- X controls for common characteristics related to expected returns (β, size, B/M, profitability, investment, momentum)
- Standard errors double clustered by year-month and firm
- In alternative specification, we delever equity return by multiplying $E_t(R_{i,t+1})$ with $(1 - L_{i,t})$, where $L_{i,t}$ is debt-to-assets

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