

Global Warming, Corporate Climate Sensitivities, and Stock Returns:

US State-Level Evidence

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Abstract:

There are growing debates on the pricing of climate risks with (dis)appearing premium demanded by investors. Employing extensive local climate data, the current study examines the market pricings of corporate climate sensitivity (CCS) with stock return predictability. Using our forecasted market-based CCS measure, the study shows that investors demand premiums when corporate stocks are exposed to global warming phenomena across the US states. Climate premium demands significantly appear when corporate stocks are prone to local disaster risk, while they remain marginally statistically significant for local transition risk. We do not observe the appearance of carbon premium for both direct and interacting effects on stock return predictions. The findings highlight the robust pricings to the systematic risks of global warming with climate premium demanded by investors. We recognize detectable premium demands for various climate risks, while our market-based CCS measures present their dominant robustness across the risk drivers over the past decades. The study complements prior literature on the (mis)pricing of climate and carbon risks, shedding light on potential research directions for future studies.

Keywords: Global Warming, Corporate Climate Sensitivities, Stock Returns, Climate Premium, Risk Factors.

JEL codes: G3.

1. Introduction.

Climate change, a public bad that is an ultimate challenge for economics (Nordhaus, 2019). According to NASA/GISS², the Earth's average surface temperature in 2023 was the warmest on record since records first started in 1880. The National Oceanic and Atmospheric Administration (NOAA) and other research organizations have produced independent studies that are aligned with NASA's analysis. Overall, the Earth's temperature in 2023 was 2.45 degrees Fahrenheit (or 1.36 degrees Celsius) higher than the preindustrial average of the late 19th century (1850–1900)³. The ten hottest years on record have been the last ten years. For the United States (US), the contiguous 48 US states' average surface temperature has increased by 0.17°F on average every ten years since 1901⁴. Since the late 1970s, average temperatures have increased more quickly, 0.32 to 0.51°F every decade since 1979. The two warmest years on record for the contiguous United States were 2012 and 2016, with nine of the ten warmest years on record having occurred since 1998. Global warming leads to diverse climate risks with profound effects and escalating consequences worldwide⁵. The main objective of the Paris Agreement is to fortify international efforts to combat climate change by limiting global temperature rise this century to well below 2 degrees Celsius above pre-industrial levels and by pursuing efforts to restrict temperature increases to 1.5 degrees Celsius.⁶

For the US, more warming has occurred in some regions than in others. For instance, temperatures have increased most in the North, West, and Alaska, whereas they have not

²data.giss.nasa.gov/gistemp/graphs/graph_data/Global_Mean_Estimates_based_on_Land_and_Ocean_Data/graph.txt

³ [Global Temperature | Vital Signs – Climate Change: Vital Signs of the Planet \(nasa.gov\)](#)

⁴ [Climate Change Indicators: U.S. and Global Temperature | US EPA](#)

⁵ [Effects - NASA Science; What are the effects of global warming? \(nationalgeographic.com\); Global warming - Climate Change, Melting Ice, Rising Sea Levels | Britannica; Global Warming of 1.5 °C — \(ipcc.ch\)](#)

⁶ [Key aspects of the Paris Agreement | UNFCCC](#)

changed much in several Southeast regions. Temperature is a basic unit of measurement used to characterize climate, and local temperatures can have diverse impacts on ecosystems and human existence. Increases in air temperature, for instance, can result in stronger heat waves.⁷, which can be fatal or cause disease, especially in susceptible groups. Seasonal and annual temperature variations also influence plants and animals in a particular area. Many different ecological processes can be affected by temperature changes, especially if they happen faster than plant and animal species can adjust. While prior literature focuses on different climate risk drivers (e.g., drought, hurricane, flooding, etc.), capturing temporary climate events (Adrian et al., 2023; Billings et al., 2022; Collier et al., 2024; Javadi & Masum, 2021; Javadi et al., 2023; Tyndall, 2023), temperature anomaly benchmarks long-term climate change given many years of greenhouse gas emissions. This study employs state-level temperature anomaly data to benchmark long-term climate change in the US, which is divergently complex across the country. In other words, we are not just benchmarking climate change in the long term but are also capturing the geographical divergence of climate change exposure across the US states.

Prior studies examine the pricing of financial markets to climate risks, which are contemporary climate events such as natural disasters (Hong et al., 2023; Huynh & Xia, 2023), physical risk using drought index (Hong et al., 2019), and transition risk using climate change news index (Huynh & Xia, 2021). In other words, prior literature fails to benchmark long-term climate change. It is critical to capture long-term climate change because all kinds of climate events result from multidecade greenhouse gas emissions. Temperature anomalies are the difference between the current temperature values for a specific location (i.e., US states) and its 30-year

⁷ [Climate Change Indicators: Heat Waves | US EPA](#)

average or more temperature values, capturing the real and long-term climate change risk. Using US state-level data temperature anomaly, this study aims to prove whether corporate climate sensitivity (a beta) related to state-level climate factors (temperature anomaly) is priced in the financial markets, becoming a new systematic risk factor. The study builds on Cuculiza et al. (2024) by developing a time-varying firm-level temperature sensitivity (FLTS) measure. Our measure is advantageously different from Cuculiza et al. (2024) as follows. While Cuculiza et al. (2024) use US nationwide temperature data to develop their FLTS measure with their self-calculated temperature anomaly, we use state-level temperature anomaly (SLTA) data provided by NCEI-NOAA to develop our state-level time-varying FLTS measure for each of our sample firms' stocks headquartered in US states. Our approaches minimize self-calculation errors of statewide temperature anomaly in predicting FLTS. Furthermore, our FLTS measure is time-varying and captures the statewide geographical divergence of corporate sensitivity to climate change for each firm's stock.

For our empirical purposes, we start with predicting state-level corporate climate sensitivity (hereafter, SL-CCS) for each firm's stock headquartered across US states. A (negative) positive value of SL-CCS indicates that a firm's stock is (negatively) positively sensitive to state-level climate change factors (hereafter, SLCC). As mentioned earlier, we benchmark SLCC by state-level temperature anomalies (SLTA), which is the difference between the current temperature value and baseline 30-year or more average values for US states where firms are located. In climate science, temperature anomaly is fundamentally critical in displaying the trend of temperature changes over time. Anomalies, as opposed to absolute temperatures, more effectively depict how the climate is changing across broader areas by indicating whether

temperatures are above or below average⁸. In one part of the world, an absolute temperature may be considered typical, while in another, it may be over average. This ambiguity over what constitutes "normal" is eliminated by anomaly, which provides data illustrating local temperature variations. Regarding the established literature on the economics of climate change (Heal, 2009, 2017; Nordhaus, 2019; Nordhaus, 1993, 2007; Stern, 2008; Tol, 2018, 2024; Weitzman, 2007), given the geographical divergence of US climatic changing conditions⁹, we employ temperature anomalies to investigate whether SL-CCS beta is priced in the US equity markets with state-level evidence, being possibly a new systematic risk factor.

Our findings show robust associations between SL-CCS and firms' stock returns (RET). The association between SL-CCS and RET is negative and significant for the full sample and negative temperature anomalies (abnormal cooler weather). The association between SL-CCS and RET becomes positive and statistically significant with positive temperature anomalies (abnormal warmth). The positive association between SL-CCS and RET is robust when we control carbon-intensive stocks (e.g., polluting firms), long-term proneness to natural disasters for firms' stocks located in disaster-prone states (DPS benchmarking long-term climate physical risks), and state-led adaptation plan finalized (SAPF for climate transition risks). Our standalone predicted associations between SL-CCS and RET are constantly robust. We do not observe positive standalone associations between DPS and RET. We only observe a positive association between DPS and RET when DPS interacts with our predicted SL-CCS (DPS x SL-CCS), indicating the moderation of global warming. Similar findings are observed for SAPF; we observe a weak and marginally positive association between SAPF and RET. An increase in

⁸ [Global surface temperature anomaly - Energy Education](#); [World of Change: Global Temperatures \(nasa.gov\)](#)

⁹ [United States - Climatology | Climate Change Knowledge Portal \(worldbank.org\)](#)

RET becomes more significant with a higher predicted magnitude when SAPF interacts with SL-CCS, specifically with positive temperature anomalies. Our findings remain unchanged when we exclude the COVID-19 pandemic and penny stocks.

Overall, our findings broadly imply that SL-CCS is priced by the stock markets, and state-level climate factors, namely positive temperature anomalies (global warming), could be acknowledged as the new systematic risk factor. Our state-level evidence suggests that the pricing of stock markets to climate risks is conditional on positive temperature anomalies (e.g., also known as global warming). Investors demand a premium to hold stocks exposed to climate risks under global warming. Also, the premium investors demand for holding stocks exposed to climate risks (climate transition versus physical drivers) is driven by temperature anomalies, for which firms are positively sensitive to global warming.

Our findings complement the emerging literature on asset pricing and climate risks. First, for the climate transition risks, we observe that the increasing sensitivity to state-level climate change (e.g., global warming) induces a premium (positive predicted stock returns) demanded by investors to hold polluting stocks (SL-CCS x RET). For panel data on monthly firms' stocks tested, we observe a negative association between SL-CCS and RET when we test for negative temperature anomalies (cooler weather). Our findings make sense in recent studies on the pricing of stock markets to corporate carbon risks (Bolton & Kacperczyk, 2021; P. Bolton & M. Kacperczyk, 2023; Shaojun Zhang, 2024). While Bolton and Kacperczyk (2021); P. Bolton and M. Kacperczyk (2023) document the presence of a carbon premium in the US and global equity markets since the Paris Agreement (COP21), Shaojun Zhang (2024) argues that the carbon premium has become negative and insignificant when test for global equity markets, which are

conditional on how stringent climate policies are. Our evidence from SL-CCS supports prior studies with the following implications. Our foremost goal is to limit global warming to 1.5°C. Greenhouse gas emissions should reach their peak before 2025 at the latest. For the US, over the recent decades, we have observed global warming across the country more clearly since the 2000s. For the contiguous US states, there are nine of the ten warmest years recorded since 1998, and the years 2012 and 2016 were the two warmest years recorded¹⁰. Our findings imply that investors demand premiums when firms are positively sensitive to abnormally positive temperatures. Even though the US has presented its changing commitments to our global climate action¹¹, with the carbon premium presented by Bolton and Kacperczyk (2021); P. Bolton and M. Kacperczyk (2023), the Paris Agreement has somehow urged investors to care about the pollution of stocks they are holding, with a subsequent premium demanded. Our evidence shows that the stock markets price carbon risks when investors feel abnormally heated. Incentives for investors to demand a premium under corporate sensitivity to state-level climate factors appear for firms' stocks located in US states that have progressive local climate action with state-led adaptation plans finalized (local climate transition risks). Our evidence aligns with Shaojun Zhang (2024), showing that the pricing of equity markets to corporate carbon risks is conditional on the stringency of environmental policies (exogenous transition risks) instead of on firms' investors. Our evidence from SLTA (state-level global warming) shows that transition risks (e.g., climate policies) present a lag from real abnormal climatic changing conditions imposed on our economy. Pooling all arguments and theoretical predictions together, the study shows that the associations between climate transition risks and stock returns are conditional on the levels of

¹⁰ [Climate Change Indicators: U.S. and Global Temperature | US EPA](#)

¹¹ [On the U.S. Withdrawal from the Paris Agreement - United States Department of State](#); [The United States Officially Rejoins the Paris Agreement - United States Department of State](#)

temperature anomalies, indicating global warming, with the subsequent climate policies to hedge systematic climate-induced risks. Our findings imply that global warming is being priced by the equity markets, possibly becoming a new systematic risk factor.

For the climate physical risks, at first glance, we do not observe any positive association between the long-term proneness to natural disasters where firms' stocks are headquartered in disaster-prone states (DPS). We even observe a negative association between DPS and RET for the full sample, which is only statistically significant when we test for negative temperature anomalies in the sub-sample. The association between DPS and RET becomes positive and significant when DPS interacts with SL-CCS (SL-CCS x DPS), implying that global warming is showing its dominant driver. Our predicted associations between SL-CCS and RET remain robust, implying that the pricing of equity markets to climate physical risks is also conditional on abnormally positive temperature change. Investors demand a premium to hold stocks where their firms are in the DPS only when they feel abnormally hot. Our findings again strengthen our argument that temperature anomalies benchmark climate change risks as our foremost climate action.¹² Our findings complement prior studies on asset pricing and physical risks, including natural disasters. (Huynh & Xia, 2023), And sea level rises (Bernstein et al., 2019; Goldsmith-Pinkham et al., 2021), showing that, combined with the proneness to natural disasters, the financial markets price climate risks when our economy experiences abnormal heat. The rationale is that global warming induces diverse kinds of severe physical risks that are documented in recent literature (Hong et al., 2019; Hong et al., 2023; Huynh & Xia, 2023), benchmarking real long-term climate change.

¹² [The Paris Agreement | UNFCCC](#)

Our study offers an important contribution to related literature. First, firms with higher temperature sensitivity earn lower returns. The negative state-level evidence of the negative association remains for the full sample and negative temperature anomalies in the sub-sample. Regarding Cuculiza et al. (2024), the findings might suggest that the performance anomaly of firms with higher temperature sensitivity does not reflect different riskiness between firms with divergent temperature sensitivity. Furthermore, such negative associations theoretically convey that market participants might not fully recognize the sensitivity of firms to temperature anomalies. This leads to the overpricing of market participants to stocks with higher temperature sensitivity, with a subsequent lower return. In other words, market participants underreact to the impacts of temperature anomalies on firms. In our state-level evidence, we find that the association between SL-CCS and RET becomes positive and statistically significant under positive temperature anomaly. The positive association is persistent even when we test for diverse climate, physical, and transition risk drivers. Our findings show that the US equity markets do price global warming with a firm's sensitivity to positive temperature anomaly. Regarding climate science, global warming leads to diverse climate risks with consequential effects on firms. Our findings support such theoretical predictions by showing that investors demand compensation for holding stocks exposed to global warming, which is a long-term consequence of climate change. More importantly, firms could be unable to effectively manage their exposure to global warming. Therefore, a firm's sensitivity to temperature anomaly, global warming with abnormally positive temperature, more specifically, has been priced by financial markets (US equity markets for our study) to become a new systematic risk-priced factor. Our study expands related streams of literature on asset pricing studies about climate risk premium by introducing a state-level temperature sensitivity of firms' stocks and demonstrating that such

firm-level temperature sensitivity to state-level long-term climate factors is empirically becoming a new systematic risk factor priced by financial markets. More importantly, the (mis)pricing of financial markets is subject to the levels of global warming, highlighting that long-term time-varying climate change, with its geographical heterogeneity, is a dominant driver of a firm's stock return. Our findings add critical complementary to theoretical predictions on the demand for climate change premiums from investors that are exposed to diverse risk drivers.

2. Literature and hypotheses.

The literature's first major result is that, while price predictions of climate risks have begun to appear in markets for durable assets like stocks, real estate, and long-term bonds, the degree of pricing varies significantly between markets and over time; for instance, a review paper by Campiglio et al. (2023).

According to today's latest report from the Intergovernmental Panel on Climate Change (IPCC), scientists are seeing changes in Earth's climate throughout the planet's climate system and in every region.¹³ A significant number of the climate change risks that have been noticed are unexpected in several thousand, if not hundreds of thousands of years, and some of the changes that have already occurred, such as the ongoing rise in sea level, cannot be reversed over hundreds or thousands of years. Bernstein et al. (2019), for instance, predicted that residential properties vulnerable to potential flooding risk would sell for roughly 7% less than unexposed but otherwise equivalent properties if the average worldwide sea level rose by six feet, as is predicted to happen by 2100.

¹³ [Climate change widespread, rapid, and intensifying – IPCC — IPCC](#)

Water cycle intensity is increasing due to climate change. This causes increased drought in many areas, as well as more rainfall and the ensuing flooding. Hong et al. (2019) investigate whether food stock prices effectively discount these risks. The authors use the Palmer Drought Severity Index to rank thirty-one countries with publicly traded food companies annually based on their long-term trends toward droughts. A nation's low trend score portends comparatively slow profit growth for its food industry. Additionally, it predicts comparatively low profits on food stocks in that nation. This predictability of returns is consistent with food stock prices undervaluing the risks associated with climate change.

According to multiple studies, the coastal real estate markets in the United States have begun to price the risk associated with the predicted surge in future flooding brought on by sea level rise (SLR)¹⁴. Baldauf et al. (2020) Investigate whether disparities in climate change beliefs are reflected in housing prices. The authors demonstrate that prices exhibit various elasticities to climate risk in an equilibrium model of housing choice, and agents derive benefit from ownership in a neighborhood of comparable agents. Utilizing extensive transaction data, the study establishes a connection between pricing, individual property inundation forecasts, and climate change belief assessments. The study discovers that, compared to homes in non-flooded neighborhoods, houses predicted to be flooded in flood-prone areas sell for less money. The findings imply that differences in opinions regarding the long-term risks of climate change are reflected in housing prices. Because of rising ocean temperatures and melting land ice, the rate of future global sea level rise is likely to increase.

¹⁴ [Sea Level Rise and Housing Markets | News | National Centers for Environmental Information \(NCEI\) \(noaa.gov\)](#)

According to Giglio et al. (2021), housing markets can offer insight into the proper discount rates to use when pricing investments in mitigating climate change. Real estate has a term structure of discount rates that slopes downward and reaches 2.6% for payoffs longer than 100 years. It is susceptible to both consumption and climate risk. Using a tractable asset pricing model that accounts for the distinctive features of climate change, the study shows that the term structure of discount rates for investments that hedge against climate change is consequently upward sloping but is bound above by the risk-free rate. The anticipated housing discount rates offer an upper bound at horizons where risk-free rates are not accessible.

Municipal bond markets started pricing higher risk of sea level rise (SLR) exposure in 2013, coinciding with upward revisions to SLR estimates (Goldsmith-Pinkham et al., 2021). Bonds with longer maturity are more adversely affected, and short-term flood risk is not a primary cause of the damage. The study uses a structural model of credit risk to quantify the predicted economic impact and distinguish between the effects of uncertainty with underlying asset prices. The SLR exposure premium is unaffected by controlling home prices, suggesting that uncertainty over the future effects of SLR has a greater impact on bond prices than lowering present asset values.

Huynh and Xia (2021) investigate whether corporate bonds are valued for the risk of climate change news. In line with the consequences of demand for bonds with a high potential to buffer against climate risk for asset pricing, the authors estimate bond covariance using a climate change news index and find that bonds with a greater climate change news beta earn lower future returns. Furthermore, investors who worry about climate risk are prepared to pay more for bonds issued by companies that have demonstrated improved environmental performance. According to

their research, corporate initiatives to enhance environmental performance are beneficial when investors are worried about the possibility of climate change. A recent study by Huynh and Xia (2023) looks at investors' responses to natural disasters in the U.S. corporate bond and stock markets. The study also examines how exposed a corporation is to physical climate risk using disaggregated establishment-level data. It has been shown that investors tend to overreact when a corporation is exposed to natural disasters, which lowers the current bond and stock prices and increases future profits. Though their fundamentals deteriorated after the disasters, companies with a high environmental reputation face less selling pressure on their bonds and equities.

For the equity markets, Bolton and Kacperczyk (2021) investigate the potential impact of carbon emissions on the US stock return cross-section. After adjusting for size, book-to-market, and other return predictors, the study finds that stocks of companies with higher overall carbon dioxide emissions (and changes in emissions) generate higher returns. This carbon premium cannot be explained by variations in unforeseen profitability or by other established risk factors. Additionally, the study discovers that in a few notable businesses, institutional investors use exclusionary screening based on direct emission intensity or the ratio of total emissions to sales. All things considered, the findings support the theory that investors are already requesting payment for the risk associated with carbon emissions. For global equity markets, firms are exposed to carbon transition risk as a result of the energy transition away from fossil fuels (P. Bolton & M. Kacperczyk, 2023). The study finds that greater stock returns are associated with higher levels and growth rates of carbon emissions in all sectors and most countries, based on our estimation of the market-based premium associated with carbon transition risk in a cross-section of 14,400 enterprises across 77 nations. Firms based in nations with less developed economies, more expansive energy sectors, and less inclusive political systems are subject to

higher carbon premia associated with emissions growth. Emissions-related priorities are greater in nations with more stringent national climate regulations. The latter has grown in tandem with investor knowledge of the risks associated with climate change.

The discussion of investments considering climate change revolves around the cost of carbon transition risk. The data in this article, which is only accessible to investors with substantial lag, shows that emissions increase linearly with firm sales (Shaojun Zhang, 2024). Rather than the risk premium, the positive carbon return, or brown-minus-green return differential, reported in earlier studies comes from the emissions' forward-looking company performance information. Carbon returns become negligible internationally and negative in the United States once the data release latency is taken into consideration. Because of strong shocks related to climate change, developed markets have lower carbon returns, whereas nations with stricter climate laws have higher carbon returns.

Prior literature focuses on climate risk drivers but misses their benchmarked climate change measure, namely, temperature anomaly. Temperature anomaly is a multi-year consequence of greenhouse gas emissions (e.g., corporate carbon emissions, etc.) for which climate risk drivers present their long-lag phenomena under global warming. For instance, economies worldwide have increasingly experienced frequent abnormal climate events, escalating in recent years. The Paris Agreement was adopted recently since 2015 for our global climate action, mitigating global warming, for which net-zero targets are our foremost climate goal by 2050. Global warming emerged in the US and worldwide some decades ago, and its phenomenon with associated climate risks is becoming more serious than ever in recent years. Pooling altogether, our main hypothesis (H) is as follows.

H1: Benchmarking long-term climate change, temperature anomaly is the principal driver of stock return.

Because global warming leads to diverse climate risk drivers with both endogenous and exogenous factors for physical versus transition risks, our additional hypotheses are as follows:

H1A: Stock returns are positively associated with global warming, for which firms are positively sensitive to temperature anomaly (warmer than normal).

H2: Climate risk drivers matter to stock returns, and investors demand premiums when their firms' stocks are positively sensitive to global warming.

Our tested hypotheses are critical to emerging literature on climate change and financial markets by benchmarking long-term climate change risks. Based on our hypotheses tested, we complement heterogeneous findings on the pricing of financial markets to climate risk drivers discussed throughout the literature review section.

3. Variables and data sources.

3.1.State-level climate change data

Regarding the established literature on the economics of climate change (Heal, 2009, 2017; McKibbin & Wilcoxon, 2002; Nordhaus, 1993, 2007; Stern, 2008; Tol, 2018, 2024; Weitzman, 2007), the study benchmarks climate change using temperature anomalies. For state-level evidence, we collect monthly statewide temperature data archives from the National Centers for Environmental Information [NCEI], and the National Oceanic and Atmospheric Administration [NOAA]. The study handles time series data archives in long format for each state's temperature

values and anomalies and transforms statewide data archives into panel data. Our monthly statewide temperature panel data includes 75,002 state-year-month observations from 1895-01 to 2023-02¹⁵ for a total of 49 US states.

3.2. Market data

The study collects data on US common stocks [Share codes 10-11] from the Center for Research in Security Prices [CRSP]. We collect monthly stock files [CRSP-MSF]¹⁶, including a total of 3,875,228 monthly stock observations¹⁷. We keep exchanging code [EXCHCD 1-3] the US primary stock exchanges [PRIMEXCH], including: 1) New York Stock Exchange, 2) American Stock Exchange, 3) The Nasdaq Stock Market (SM)¹⁸. We remove financial firms' stocks [SICCD 6000-6999]. We generate CRSP useful variables following CRSP's guidance for handling the "Negative" Prices, Adjusting Prices and Shares for Splits, Returns with Dividends, Delisting Returns, and Market Capitalization¹⁹. We generate a quarter variable based on the date variable that CRSP provided us. Our processed CRSP-MSF data includes 3,203,886 monthly stock observations. We drop stock prices [PRC] less than one and remove stock returns [RET] with missing values. For setting panel data with CRSP-MSF files, we drop the repeated values for the date variable for each of our sample firms' stocks. With additional processing steps, our CRSP-MSF processed file includes 2,484,482 monthly stock observations.

¹⁵ State-level climate data archives were extracted, handled, and processed as of 2023-04-01.

¹⁶ CRSP-MSF was extracted as of 2024-02

¹⁷ For the raw CRSP-MSF file: Variables: 64. Observations: 3,875,228. Size 1,788.72M. Memory: 2,144M. Created: Wednesday, 21 February 2024, 8:51:23 pm [New Zealand time]. Size: 1.74 GB (1,875,651,850 bytes). DTA File (.dta) labeled 'crsp_msf.dta'.

¹⁸ Code Exchange: N for NYSE; A for AMEX; Q for NASDAQ; X for Other Exchange; R for ARCA

¹⁹ See, [Wharton Research Data Services \(upenn.edu\)](https://www.wharton.upenn.edu/research/data-services/)

3.3. Fama-French Five Factors [FF5] data.

The study collects historical data for the five factors of Fama and French (2015) [FF5] from the authors' website²⁰. We merge FF5 data with CRSP-MSF files that generate a merged file with 2,794,196 observations matched. We keep only matched observations for the CRSP-MSF-FF5 merged data.²¹ We then merge the CRSP-MSF-FF5 merged data with the US national monthly time series that generates a merged file with 2,772,319 month-stock observations. We again keep only matched observations.²²

3.4. Firm-level fundamentals.

The study extracts corporate fundamentals from the COMPUSTAT Quarterly file. We merged the COMPUSTAT Quarterly file with the CRSP-MSF-FF5 and merged monthly data using CUSIP, quarter, and year variables. The merging step generates a total of 559,321 matched observations. We also collect monthly firm-level financial ratios from the WRDS (Beta) database.²³ and merge it with CRSP_MSFF stock files, Fama-French 5 Factors, and US statewide and nationwide climate monthly merged file. This merging procedure generates a total of 411,894 stock-month observations.

²⁰ Historical Data - Fama/French 5 Factors (2x3) extracted at
https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_5_factors_2x3_archive.html. Downloaded the file
"July 2023 Data CSV" at
https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/Historical_Archives/08%202023%20Update/ftp/F-F_Research_Data_5_Factors_2x3_CSV.zip

²¹ It is saved as 'crsp_msf_processed_ff5.dta'

²² 22,699 observations deleted and the merged file is saved as 'crsp_msf_processed_ff5_climate.dta'

²³ Financial Ratios Suite by WRDS is the latest addition to the WRDS analytics platform. It's a web-based engine that delivers over 70 pre-calculated financial ratios for all U.S. companies across eight different categories (Valuation, Liquidity, Profitability, and etc).

3.5. Other data archives

We collect data on the 3-Month Treasury Bill Secondary Market Rate, Monthly Discount Basis (TB3MS), from FRED²⁴.

4. Estimation methods and empirical models.

4.1. Predicting state-level corporate climate sensitivity

The study starts predicting state-level corporate climate sensitivity for each sample firm's stocks in each US state using state-wide climate-stock monthly data. The study measures the state-level corporate climate sensitivity by regressing stock excess return on the market factor and state-level temperature anomaly. The study estimates the regression model for each of the sample stocks in our sample as follows:

$$R_{i,s,t} - R_{F,t} = \alpha_{i,s,t} + \beta_{i,s,t}(R_{Mkt,t} - R_{F,t}) + \beta_{i,s,t}SLCC_{s,t} + \varepsilon_{i,s,t} \quad (1)$$

The characters of i , s , and t indicate a firm's stock i headquarter location in a US State s at time t (monthly basis). $R_{i,s,t}$ is a monthly stock return. $R_{F,t}$ is the risk-free rate using the 3-Month Treasury Bill Secondary Market Rate, Discount Basis - TB3MS. $R_{Mkt,t}$ is the market return is proxied by the CRSP value-weighted return, including dividends.

State-level climate change (SLCC) is proxied by the monthly state-level temperature anomaly [SLTA] in state s in month t . Temperature anomalies are more significant than absolute temperature in studies on climate change (NCEI, 2024). The deviation from the average, or

²⁴ <https://fred.stlouisfed.org/series/TB3MS>

baseline, temperature is known as a temperature anomaly. Usually, 30 or more years' worth of temperature data are averaged to determine the baseline temperature for US states. For each US state, a positive anomaly denotes a temperature difference between the observed and baseline values, whereas a negative anomaly denotes a temperature difference between the two values. For each stock, we employ the regressions with a 60-month rolling window. After matching multiple datasets and processing steps, our monthly stock-level data includes 363,022 state-stock-month observations from 1985 to 2023. We frequently come across references to temperature anomalies when investigating global climate change and temperature data²⁵. That is the discrepancy between the actual temperature and the long-term average temperature, also referred to as a reference value. The predicted long-term average temperature is represented by the anomaly for each US state, which is the deviation from the expected value. A positive anomaly denotes a temperature warmer than normal for US states, whereas a negative anomaly denotes a temperature cooler than usual for US states²⁶.

The predicted $\beta_{i,s,t}$ captures the predicted corporate sensitivity to state-level climate change (state-level temperature anomaly) for stock i at time t in state s . The positive (negative) $\beta_{i,j,t}$ implies that the excess return of a specific stock i is positively (negatively) associated with the temperature anomaly in the month t in the state s where that firm's stock is headquartered. We present a histogram of the State-Level Corporate Climate Sensitivity [SL-CCS] predicted with a kernel density estimate $\beta_{i,s,t}$ in Figure 5. From this stage onward, we use the SL-CCS predicted beta for our regressions of stock returns [RET] on SL-CCS to prove whether our predicted

²⁵ [Temperature Anomalies \(cct.edu\)](https://climate.nasa.gov/evidence/#anomalies)

²⁶ See also, [NASA SVS | Global Temperature Anomalies from 1880 to 2022](https://climate.nasa.gov/evidence/#anomalies); [Global Temperature | Vital Signs – Climate Change: Vital Signs of the Planet \(nasa.gov\)](https://climate.nasa.gov/evidence/#anomalies)

statewide firm-level climate sensitivity (a beta) to state-level climate factor (here is SLTA) is priced in the financial market (the US equity markets for the current study) that could become a new systematic risk priced factor.

It is inevitable to acknowledge that the pricing of climate risks for durable assets (e.g., stocks, bonds, real estate, etc.) has been increasingly attractive to asset pricing literature. For the equity markets more specifically, we find the ongoing debate about whether a carbon premium exists to reflect the pricing of stock markets to transition risks (Aswani et al., 2024; Bolton & Kacperczyk, 2021; P. Bolton & M. Kacperczyk, 2023). Cuculiza et al. (2024) provide evidence from firm-level temperature sensitivity (FLTS or TS) using a time-varying measure to examine the association between temperature changes and firm performance. The study posits that high FLTS is associated with lower future profitability in riskier corporate policies. The study explains that such high-CS firms are overpriced with their lower future returns, and there is potentially a mispricing by market participants. The study shows that high-CS firms exhibit greater portfolio weights from non-local institutional investors, and sell-side equities analysts make fewer accurate projections for these firms. Collectively, the study implies that predictable patterns in returns are produced when financial markets underreact to firm-specific information regarding temperature changes. Between 1968 and 2020, the study finds that an annualized risk-adjusted return of more than 4% is produced by a trading strategy with mispricing.

Since the climatic conditions and their anomalies are divergent across the US, the study by Cuculiza et al. (2024) employs U.S. national temperature data that might miss the geographical

heterogeneity of climate change across the US states²⁷. Based on US national temperature data, the study also implements self-calculations for temperature anomaly that might generate unexpected calculation errors²⁸. It is acknowledged by the study that although temperature variations at the local or regional level may offer a more accurate representation of the changes experienced by the company, the increased level of detail may potentially underestimate the effects of these changes on specific kinds of businesses. For example, temperature variations away from corporate headquarters may have an impact on geographically distributed businesses and those with extensive distribution networks. Furthermore, non-local temperature variations may have an impact on the geographically scattered clients and suppliers of multiple businesses. However, firms' headquarters could be centrally vulnerable to local temperature anomalies, with abnormal climatic phenomena leading to subsequent impacts on their distribution networks. Also, for predicting local firm-headquartered temperature sensitivity (LFHTS), we at least have already controlled local climate factors that a firm is prone to instead of the whole US geography. For instance, some parts of the US experience more extreme weather and abnormal temperatures than other regions²⁹. Collectively, we hereby build a step forward contributing to Cuculiza et al. (2024) by directly employing state-level temperature anomaly data to estimate state-level corporate climate change sensitivity (SLCCS, or known as state-level corporate temperature anomaly sensitivity – SLCTAS beta)³⁰. We then examine its associations with stock returns (RET) to prove whether our corporate climate change sensitivity (an SLCCS beta) linked

²⁷ See Table A1 Variable Definitions Cuculiza, Carina and Kumar, Alok and Xin, Wei and Zhang, Chendi, Temperature Sensitivity, Mispricing, and Predictable Returns (April 11, 2024). SSRN: <http://dx.doi.org/10.2139/ssrn.3331872>

²⁸ See Section 2.1. Temperature Data.

²⁹ [Climate Change Indicators: U.S. and Global Temperature | US EPA](#); [Climate Change Indicators: High and Low Temperatures | US EPA](#).

³⁰ We use the terms interchangeably with the same meaning because temperature anomalies benchmark climate change, as discussed in detail earlier.

to state-level climate factor (here is SLTA) is priced in the financial market, US equity markets more specifically, becoming a new systematic risk factor. We support our main hypotheses with the following arguments. First, the associations between SLCCS beta and RET are conditional on SLTA. Furthermore, the associations between SLCCS beta and RET become positive under positive SLTA.

The rationale is that global warming (positive abnormal temperatures induces diverse and complex climate risk drivers. The temperature of our world is rising. Earth has warmed by 1 degree Celsius, or around 2 degrees Fahrenheit, since the Industrial Revolution, which sparked the use of fossil fuels in everything from power plants to transportation. Whilst that might not seem like much, 2023 was the hottest year in history.³¹ The last ten warmest years ever recorded have all happened within the past ten years. According to a reconstruction of Earth's average temperature over the previous 485 million years, major extinctions and catastrophic weather occur when the globe warms (Pedersen et al., 2021)³². Therefore, we argue that SLTA is the main driver of the associations between SLCCS beta and RET, compared to other climate risk factors, and is a new systematic risk factor. Also, the new systematic risk factor (SLCCS beta) is significantly priced in US states that are prone to natural disasters (physical risk), having local climate action (transition risk).

Our additional hypotheses aim to test the rationale that global warming (abnormal warmer temperature or positive temperature anomaly) is a long-term consequence of many years of

³¹ [2023 was the world's warmest year on record, by far | National Oceanic and Atmospheric Administration \(noaa.gov\)](#); [Assessing the Global Climate in 2023 | News | National Centers for Environmental Information \(NCEI\) \(noaa.gov\)](#)

³² Although the terms global warming and climate change are frequently used interchangeably, scientists prefer to refer to the complex changes currently influencing our planet's weather and climate systems as "climate change.", see [Climate Change Coverage \(nationalgeographic.com\)](#)

greenhouse gas emissions. Therefore, the sensitivity of firms, investors, and stakeholders could long lag what the earth has experienced over many years. The awareness of investors and financial markets' pricing of climate risks has just emerging in recent years, for instance (Ilhan et al., 2023; Krueger et al., 2020). Physical risks have become more frequent with higher severity. At COP21 in Paris on December 12, 2015, nations ratified the Paris Agreement to combat climate change. Less than a year later, the Agreement came into effect. All nations are committed to working toward keeping the rise in global temperatures well below 2 degrees Celsius and, considering the serious hazards, aiming for 1.5 degrees Celsius. For the US, states, and communities around the country have begun to prepare for climate change, and this planning process typically results in a document called an adaptation plan³³. Environmental policies are becoming more stringent across the world's economies (OECD, 2024). After decades of global warming starting in the US and globally, with escalating severity caused by frequent physical risks³⁴, our human actions (e.g., climate policies, sustainability initiatives, strategies, investments, etc.) have followed to combat climate change, which is acknowledged as the transition risk³⁵. Even though physical risks have become severe with higher frequency and significant losses (physical risks), and our awareness of urgent actions needed to combat climate change risks, global warming (positive temperature anomaly) started several decades ago³⁶. Therefore, global warming should be acknowledged as the main driver for financial markets' pricing of climate risk drivers that come well after.

³³ [U.S. Department of State 2024-2027 Climate Adaptation Plan \(sustainability.gov\)](#); [State and Local Adaptation Plans - Georgetown Climate Center](#); [How much progress is the world making to tackle climate crisis? | World Economic Forum \(weforum.org\)](#)

³⁴ [Billion-Dollar Weather and Climate Disasters | National Centers for Environmental Information \(NCEI\) \(noaa.gov\)](#); [A record 63 billion-dollar weather disasters hit Earth in 2023 » Yale Climate Connections](#)

³⁵ [Climate policy success depends on transition risk mitigation | World Economic Forum \(weforum.org\)](#)

³⁶ [What Is Climate Change? - NASA Science](#); [Global Temperature | Vital Signs – Climate Change: Vital Signs of the Planet \(nasa.gov\)](#)

4.2. Empirical models.

We run regressions of stock returns on SL-CCS betas by proposing the following regression model:

$$RET_{i,s,t} = \alpha + \beta_1 SL - CCS_{i,s,t} + \beta_k \sum_{i=0}^n X_{i,s,t} + \varphi_t + \omega_{SICCD} + \delta_i + \varepsilon_{i,t} \quad (2)$$

The main dependent variable is stock return (RET). The main independent variable is the SL-CCS beta predicted by Equation 1, capturing state-level corporate climate sensitivity. Based on the literature on stock returns and determinants, we include a vector of diverse control variables X . Our control variables include firm size (SIZE), book-to-market (BM), financial leverage (LEV), Tobin's Q ratio (Q), capital expenditure (CAPEX), corporate tangibility (TANG), return on assets (ROA), revenue (SALE), R&D expenditure (R&D), and cash holdings (CASH). We include fixed effects for time/month φ and industry/SICCD ω with standard errors clustered for firms δ . ε is the error term. For the baseline regressions (Equation 2), we respectively run regressions of RET on SL-CCS beta and controls for the full sample, with negative and positive temperature anomalies.

Next, we discuss the channeling effects of potential climate risk drivers by proposing an additional regression model.

$$RET_{i,s,t} = \alpha + \beta_1 SL - CCS \times M_{i,s,t} + \beta_2 SL - CCS_{i,s,t} + \beta_1 M_{i,s,t} + \beta_k \sum_{i=0}^n X_{i,s,t} + \varphi_t + \omega_{SICCD} + \delta_i + \varepsilon_{i,t} \quad (3)$$

All else equal to Equation 2, we respectively examine the moderation M for climate risk drivers. The first moderator is the pollution of firms' stocks (POLLUTING STOCKS). We classify polluting stocks (labeled 1) based on the Global Industry Classification Standard (GICS) for firms' stocks that belong to Energy, Materials, Industrials, and Utilities (otherwise, labeled 0)³⁷. Regarding the literature, corporate carbon emissions are exposed to transitional risk in the era of climate change, for which investors might demand carbon premiums to hold stocks polluting the environment. Our global economy is transitioning to a carbon-neutral economy by 2050; given increasing climate policy stringency, polluting firms are subject to a greater sensitivity to climate transition risk. For the US state-level/local transitional risk, we employ state-led adaptation plans finalized (SAPF), a dummy variable that is set equal to 1 if a specific US state has adopted its SAPF; otherwise, it is set to 0³⁸. For climate physical risk drivers, we employ disaster-prone states (DPS). DPS is a dummy variable that is set equal to 1 for states that are chronically prone to natural disasters; otherwise, DPS is set equal to 0. We extensively control diverse climate risk drivers to investigate their potential channeling effects on the pricing of stock markets to the sensitivity of firms' stocks to global warming. Our approach offers more insightful and thorough investigations of climate risk factors with minimal biased estimations and interpretations.

5. Empirical findings and discussions.

[Table 1 Inserted about Here]

Table 1 reports the descriptive statistics of variables for our full sample. Our sample includes approximately 340,000 observations. For instance, SL-CCS, the main independent variable

³⁷ For details, please direct to [GICS® - Global Industry Classification Standard - MSCI](#)

³⁸ For progress tracker update, please visit [State and Local Adaptation Plans - Georgetown Climate Center](#)

capturing state-level corporate climate sensitivity beta, has 340,513 state-firm-stock-year-month observations with mean and median values of 0.000, ranging from -0.047 (minimum value – Min) to 0.050 (maximum value - Max). SL-CCS presents its standard deviation (SD) of 0.012. A positive value of SL-CCS indicates that firms' stocks are positively sensitive to temperature anomalies, while a negative value of SL-CCS indicates that firms' stocks are negatively sensitive to temperature anomalies. (Negative) Positive temperature anomalies indicate that the climate is (cooler) warmer than its 30-year or more average temperature in a particular US state. A positive SL-CCS beta shows that a firm's stock is sensitive to warmer-than-normal temperatures, which is global warming across the US states. While the mean and median values of SL-CCS surround zero, for our full sample, we find that its SD is positive, having a value of 0.012. Also, the maximum value of SL-CCS is positive, having a value of 0.050, which is higher than its minimum value of -0.047. The initial statistics show that firms' stocks have been sensitive to positive temperature anomalies, in which our SD shows that SL-CCS deviates positively from its mean value. In other words, the amount of variation of SL-CCS is positively variable in our full sample, showing that firms' stocks are likely sensitive to positive temperature anomalies in the US states.

Our dependent variable, capturing firms' stock returns (RET), has a total of 356,887 observations with a mean value of 0.007 and a median value of 0.000. RET ranges from a minimum value of -0.441 to a maximum value of 0.660 with an SD of 0.170. Our alternative dependent variable, capturing excess stock returns ($R_i - R_f$), has the same number of 356,887 observations with a mean value of -3.184. the excess returns range from -3.184 (Min) to 0.208 (Max) with an SD of 2.365 and a median value of -3.392. Reflecting on our descriptive statistics, compared to

Cuculiza et al. (2024), we observe the following critical distinctions³⁹. First, the most important one, the predicted temperature sensitivity is positive for all its statistical values, with no minimum or maximum values reported. Should all firms' stocks be positively sensitive to nationwide temperature anomalies? Also, the statistical values of temperature sensitivity are higher than our state-level current study. As elaborated throughout the study, the US presents its statewide geographical climatic conditions as well as its abnormal values. Therefore, it is critical to predict the state-level sensitivity of stocks for firms' headquarters. Second, the full sample of Cuculiza et al. (2024) presents a total of roughly 2,2 million observations. With no filtering steps reported, the sample of Cuculiza et al. (2024) might include penny stocks as well as non-common stocks listed outside major stock exchanges. Hence, both the number of observations and descriptive statistics might be inadvertently inflated, leading to potentially biased results and interpretations. In Figure 5, we present our predicted US state-level corporate climate sensitivity in its logarithmic value.

[Tables 2 & 3 Inserted about Here]

The baseline regressions show that state-level corporate climate sensitivity [SL-CCS] is strongly associated with stock returns [RET], as reported in Table 2. The association between SL-CCS and RET is negative for the full sample and negative temperature anomaly (Columns 1& 2). The association becomes positive when the temperature anomaly is positive (Column 3). The predicted associations between SL-CCS and RET remain unchanged when we include control variables (Columns 4-6), excluding the COVID-19 pandemic (Table 3). The baseline findings

³⁹ Table 1, Page 46 of Cuculiza, Carina and Kumar, Alok and Xin, Wei and Zhang, Chendi, Temperature Sensitivity, Mispricing, and Predictable Returns (April 11, 2024). Available at SSRN: <https://ssrn.com/abstract=3331872> or <http://dx.doi.org/10.2139/ssrn.3331872>

imply that climate sensitivity (beta) to state-level climate factors is priced in the stock markets. The pricing of stock markets to SL-CCS is driven by positive temperature anomalies, indicating that global warming across the US states could be acknowledged as a new systematic risk factor. The findings complement prior studies on the asset pricing of climate risks by showing that climate sensitivity (beta) to state-level climate factors is priced in the stock markets, conditional on global warming (positive temperature anomaly/abnormal warmer temperature). The rationale is that warmer temperatures induce changes in climate patterns that disrupt the common norms of our nature⁴⁰. Furthermore, temperature is the most important climatic element used for our decision-making⁴¹. Since the beginning of the 20th century, the contiguous United States' yearly average temperature has increased. Overall, the temperature rose until roughly 1940, fell until 1970, and then rose again until 2016 (Vose et al., 2017). Storms, heat waves, floods, and droughts are just a few of the disasters that are getting worse due to rising temperatures. Warmer temperatures provide an atmosphere with an increased capacity to absorb, hold, and release water, altering weather patterns with various climate consequences⁴². Our baseline findings imply that RET is positively associated with climate sensitivity (beta) when the US contiguous states experience positive temperature anomalies. Our findings show that state-level corporate climate sensitivity to temperature anomaly is priced by the stock markets, becoming a new systematic risk factor when temperatures are abnormally warmer.

[Table 4 Inserted about Here]

⁴⁰ [Causes and Effects of Climate Change | United Nations](#)

⁴¹ [Temperature Changes in the United States - Climate Science Special Report \(globalchange.gov\)](#)

⁴² [Consequences and Effects of Global Warming -- What is the Impact? \(nrdc.org\)](#)

Controlling the polluting stocks, we do not observe significant findings for the interaction terms between CL-CCS and a dummy binary variable capturing polluting stocks. The predicted associations between SL-CCS and RET remain unchanged when we control polluting stocks (Table 4). Our findings imply that climate sensitivity (beta) to state-level climate factors is priced in the stock markets, conditional on global warming. Investors demand a premium for holding stocks exposed to positive temperature anomalies. Focusing on the pricing of climate transition risk, prior studies theoretically argue that brown firms are exposed to transition risk (e.g., climate policies) toward our net-zero target. Hsu et al. (2023) argue that brown firms are likely to earn higher expected returns. Pástor et al. (2022) show that green assets have presented high returns in recent years, reflecting unexpectedly strong increasing environmental concerns. Bolton and Kacperczyk (2021); P. Bolton and M. Kacperczyk (2023) document existing carbon premiums, indicating that equity markets are pricing carbon transition risks. In et al. (2023); Pástor et al. (2022); Pedersen et al. (2021) show that green stocks present a better performance in U.S. equity, corporate bonds, and global equity markets, suggesting a continuous shift towards the carbon-conscious equilibrium. The association between carbon risk and stock returns could be contemporaneous due to the forward-looking firm performance accounted for in corporate emissions instead of a risk premium. (Shaojun Zhang, 2024). As Shaojun Zhang (2024) argues, carbon returns might become negative and insignificant for the US and global equity markets. Also, the study mentions that developed markets exhibit lower carbon returns due to severe shocks related to climate concerns, while countries with more climate policy stringency experience higher carbon returns. While the pricing of climate transition risk is subject to other transition risk drivers (e.g., policies), forward-looking performance, and scaling issues (Aswani et al., 2024; Shaojun Zhang, 2024). Prior studies show heterogeneous findings on the pricing for

financial markets to carbon risk, for which firms are in an additional period to cut their carbon emissions.

Our evidence complements prior studies by showing that the pricing of equity markets to climate risks is subject to global warming, to which firms are equally exposed. While the pricing of equity markets to the sensitivity of firms' stocks to temperature anomaly is robustly unchanged, we do not observe any significant findings when we control for polluting stocks. Similar insignificant findings are observed for the standalone polluting stocks. Our findings provide the following critical complement to related literature. First, global warming and firms' sensitivity to state-level climatic abnormal factors are the dominant drivers of stock returns. Under abnormal positive temperature anomalies, investors demand a premium when their portfolios of firms' stocks are exposed to abnormally warmer temperatures. In the same vein as S. Zhang (2024), the carbon premium demanded for polluting stocks does not appear and becomes negative when we interact with our SL-CCS beta. Our findings imply that the pricing of financial markets to climate risks with carbon returns is our conditional externality (e.g., environmental policy stringency, etc.). For this study, we show that investors demand a premium when their firms' stocks are sensitive to state-level climate long-term factors, namely temperature anomalies. Pooling altogether, our findings present the pricing of equity markets with long-term climate change. More importantly, we also control its geographical and time-varying divergence across the US states.

[Table 5A Inserted about Here]

Global warming leads to diverse climate risk drivers documented in the emerging asset pricing literature. Our findings so far have affirmed the pricing of US equity markets to state-level long-

term climate change. To support our argument that global warming is the main driver of stock returns, with investors' demand for a premium only when their firms' stocks are exposed to positive temperature anomaly, we test for the potential moderation of physical and transition climate risk drivers. To capture climate physical risks, we employ US disaster-prone states (DPS), a dummy variable capturing the long-term proneness to natural disasters for US states. We employ the US State-Led Adaptation Plans Finalized, local state-level climate action for the US states, capturing climate transition risks.

As reported in Table 5A, the findings show that equity markets price SL-CCS for firms' stocks located in the DPS⁴³. The findings from the interactions between SL-CCS and DPS (SL-CCS x DPS) show that investors demand a premium to hold stocks for which their firms are prone to natural disasters. The interaction terms are positive and statistically significant when we test for the full sample (Column 1) and a sub-sample of negative temperature anomalies (Column 2). The interaction term becomes negative and statistically insignificant when we test a sub-sample with positive temperature anomalies (Column 3). The standalone effects of DPS on RET are statistically insignificant for all the fitted models, which is negative, and only statistically significant for the sub-sample of negative temperature anomalies (Column 2). The standalone associations between SL-CCS and RET remain consistent with the predicted signs and statistically significant levels. Our findings imply that equity markets are pricing climate risks, but the pricing is conditional on the levels of global warming. In other words, we observe a

⁴³ Regarding [The Most Disaster-Prone States in the U.S. \(usnews.com\)](https://www.usnews.com/story/news/2021/05/20/disaster-prone-states), Disaster-Prone States include: 1. Texas, 2. California, 3. Oklahoma, 4. Washington, 5. Florida, 6. Oregon, 7. New York, 8. New Mexico, 9. Arizona, 10 (tie). Colorado, 10 (tie). Nevada

strong positive association between SL-CCS and RET when temperatures are abnormally warmer than their long-term baseline values.

Using SL-CCS beta with firm-level environmental performance (e.g., industry-classified pollution levels) and controlled natural disasters (DPS), our findings offer critical complements to the literature. Huynh and Xia (2023) document that, if firms are exposed to disaster risks, their future returns are predicted to be significantly higher for both bond and stock markets⁴⁴. The study argues that investors overreact to disaster risks, depressing stock and bond prices, leading to higher predicted returns. Overall, the study of Huynh and Xia (2023) concludes the relationship between disasters and future returns $[RET_{t+1}]$. Using the SL-CCS beta, our findings show a negative and statistically significant relation between SL-CCS and RET. More importantly, the associations between SL-CCS and RET become positive and significant when global warming emerges across the US states. Our findings do not show significant findings when we test for one-month-ahead returns (RET and Excess RET). Conditional on global warming (e.g., abnormal warmer temperatures), our predicted associations between RET and SL-CCS are constant when we follow the estimations of Bolton and Kacperczyk (2021) using time [month] and industry [SICCD] fixed effects with standard errors clustered for firms' stocks. Our findings are unchanged when we use excess return $[Ex-RET_t]$, and the estimations show no significant findings when we test for one month ahead $[Ex-RET_{t+1}]$ as implemented in Huynh and Xia (2023).

Figure 5 presents a histogram with a kernel density estimate for the SL-CCS. The figure presents the normal distribution of our predicted SL-CCS beta with values ranging from -0.05 (minimum)

⁴⁴ Reported in Table 3 Panel A.

and 0.05 (maximum). The positive values indicate that stock returns are positively associated with state-level climate change [SLCC], proxied by state-level temperature anomalies [SLTA]⁴⁵. Overall, our findings show that the relationship between stock returns and climate risks varies by the level of corporate climate sensitivity to temperature anomalies. We only observe a positive predicted relation between SL-CCS and RET with positive abnormal temperatures, for which global warming is emerging. Our findings imply that state-level climate factors (e.g., temperature anomalies used for this study) are being priced in the financial markets (e.g., US stock markets for this study), and the pricing is conditional on SL-CCS being a systematic risk factor, namely, global warming.

[Table 5B Inserted about Here]

Next, we examine the potential moderation of local climate action (transition risk) to the association between SL-CCS and RET, as reported in Table 5B. Using state-level adaptation plans finalized (SAPF), the findings show a positive relation between the interaction term (SL-CCS x SAPF) and RET. The standalone relation between SAPF and RET is positive for all the fitted models and is only statistically significant for the full sample (Column 1) and positive anomaly (Column 3). The standalone association between SL-CCS and RET remains constant when we control SAPF. More importantly, the relation between the interaction term (SL-CCS x SAPF) and RET is positive with a stronger statistically significant level at the 5% level (Column 3 for positive temperature anomaly) compared to a 1% significant level (Column 3 for the full sample).

⁴⁵ We use SLCC and SLTA interchangeably for the study with the same meaning.

Overall, our findings convey critical insights into the pricing of financial markets to global warming (abnormally positive temperature values) at the state level. First, equity markets price climate risks, but the pricing of the markets to climate risks is conditional on the levels of global warming. Our findings are robust when we check climate-related risk drivers tested in prior asset pricing literature, including climate physical (DPS) and transition risk (SAPF) drivers. Second, our findings suggest that investors demand a premium for holding stocks exposed to global warming. The premium demand is more pronounced for firms' stocks sensitive to local state-level climate action (e.g., transition risks). We do not observe any significant findings from polluting stocks (e.g., carbon transition risks). Investors demand a premium for holding firms' stocks sensitive to disaster-prone states for the full sample test and negative temperature anomalies. We argue that the pricing of equity markets to climate risks is inevitable, and the SL-CCS predicted beta could be acknowledged as a systematic long-term risk factor. SL-CCS is also conditional on the levels of proneness of firms' locations to climate risk drivers. Either transition (endogenous versus exogenous factors) and physical risks (long-term vs short-term), our findings predict constant associations between RET and SL-CCS predicted betas to capture the sensitivity of firms' stocks to state-level and long-term climate change benchmarked by temperature anomalies. Our findings complement prior asset pricing literature on climate change, showing that the sensitivity of firms' stocks to long-term climate change is a principal driver of stock returns. Our findings are robust with(out) the COVID-19 pandemic, penny stocks, and using either stock return or excess returns as used in prior literature. The study reports the detailed tables in the appendix section for additional empirical insights and robust validations.

6. Conclusion

Taking advantage of such critical research gaps, the study predicts state-level corporate climate sensitivity (SL-CCS). Using the uniquely predicted SL-CCS betas, the study examines the pricing of US stock markets to the sensitivity of firms to local climate factors, becoming a potential priced factor in climate-related empirical asset pricing literature. Benchmarking long-term climate change with statewide temperature anomaly, the study shows that the pricing of stock markets to SL-CCS beta is conditional on global warming, the benchmarked long-term climate change risk measure. More specifically, the associations between SL-CCS betas and stock returns are only positive and statistically significant under positive temperature anomalies. The rationale is that global warming leads to diverse climate risk drivers and investors' awareness of climate risks is clear when their firms' stocks are exposed to abnormally warmer temperatures. While prior studies claim that RET is positively related to climate risk factors due to the depression of investors to prices, the study shows that long-term climate change is a principal driver of the presence of global warming as a new systematic risk. Without controlling for our SL-CCS betas, the study finds weak evidence on the proper pricing of equity markets to climate risk drivers which is heterogeneously documented in prior literature (Aswani et al., 2023a, 2023b; Bolton & Kacperczyk, 2021; Patrick Bolton & Marcin Kacperczyk, 2023a, 2023b; Shaojun Zhang, 2024). The rationale is that prior studies may fail to benchmark climate change risks with their geographically complexity. To test the hypothesized rationale, interacting with our predicted SL-CCS beta with carbon-intensive stocks to capture endogenous transition risk, we find no evidence of the presence of carbon premium for polluting stocks. For exogenous transition risk, the study finds weak evidence on the association between state-led adaptation plans finalized (SAPF) and stock returns (RET). The SAPF-RET nexuses are marginally positive

and statistically significant for the full sample and become stronger in terms of predicted value and significant levels when we interact SAPF with SL-CCS beta and test for positive temperature anomalies in the sub-sample. Controlling for the long-term proneness to natural disasters, we even find a negative and statistically significant association between RET and disaster-prone states (DPS) under negative temperature anomalies and no significant RET-DPS nexus detected under positive temperature anomalies. The predicted RET becomes positive and significant when we interact DPS with SL-CCS beta (DPS x SL-CCS) for the full sample and negative temperature anomaly as the sub-sample. The study thoroughly controls for diverse climate risk drivers to consolidate our tested hypotheses. The study empirically proves that the sensitivity of firms' stocks to state-level and long-term climate change is being priced by the US stock markets that could become a new systematic risk factor. The study finds strong evidence that state-level global warming is a dominant driver of stock returns with possible premiums demanded by investors for holding stocks exposed to long-term climate change. Capturing the geographical divergence of climate change in the US, the third chapter complements prior literature on asset pricing and climate-related risks with heterogeneous findings (Aswani et al., 2024; Bolton & Kacperczyk, 2021; P. Bolton & M. Kacperczyk, 2023; Huynh & Xia, 2021; Huynh & Xia, 2023; S. Zhang, 2024). The tested hypotheses suggest that the sensitivity of firms' stocks to long-term climate change is the main driver of stock returns. Furthermore, the findings show that investors only demand a premium when their firms' stocks are exposed to global warming (e.g., state-level positive temperature anomaly). There is weak evidence on the other climate risk drivers driving stock returns with premiums demanded by investors that are documented in the literature. The predicted SL-CCS betas offered by the study are crucial to future asset pricing literature on the reliable pricing of financial markets to climate risk factors.

Table 1: Descriptive statistics [Full sample]

Variable	N	Mean	Min	p50	Max	SD
RET	356887	0.007	-0.441	0.000	0.660	0.170
Ri-Rf	356887	-3.184	-8.213	-3.392	0.208	2.365
SL-CCS	340513	0.000	-0.047	0.000	0.050	0.012
SLTA	352325	1.303	-16.000	1.000	18.000	3.326
SIZE	282516	4.931	0.054	4.909	11.005	2.521
BM	230148	1.351	0.014	0.897	9.092	1.574
LEV	263073	0.311	0.000	0.185	4.104	0.528
Q	244399	3.006	0.455	1.367	51.796	6.347
CAPEX	255570	0.034	0.000	0.014	0.343	0.057
TANG	272632	0.259	0.000	0.156	0.950	0.270
ROA	274833	-0.041	-1.575	0.008	0.131	0.210
SALE	278721	0.216	0.000	0.154	1.160	0.228
R&D	362254	0.011	0.000	0.000	0.510	0.044
CASH	279224	0.181	0.000	0.070	0.974	0.241

The table reports statistical descriptive values of the variables used for our merged sample.

Table 2: State-level corporate climate sensitivity [SL-CCS] and stock returns [RET]						
VARIABLES	(1) RET Full sample	(2) RET Negative Anomaly [Abnormal Cooler]	(3) RET Positive Anomaly [Abnormal Warmer]	(4) RET Full sample	(5) RET Negative Anomaly [Abnormal Cooler]	(6) RET Positive Anomaly [Abnormal Warmer]
SL-CCS	-0.261*** (0.035)	-2.548*** (0.068)	0.840*** (0.044)	-0.300*** (0.047)	-2.657*** (0.091)	0.784*** (0.061)
SIZE				-0.000** (0.000)	-0.000 (0.000)	-0.000 (0.000)
BM				-0.000 (0.000)	-0.000 (0.001)	0.000 (0.000)
LEV				0.001 (0.001)	0.004** (0.002)	-0.000 (0.001)
Q				-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
CAPEX				0.011 (0.009)	0.016 (0.016)	0.008 (0.011)
TANG				-0.004** (0.002)	-0.007* (0.004)	-0.003 (0.002)
ROA				0.002 (0.003)	0.010 (0.006)	0.002 (0.003)
SALE				-0.002 (0.002)	-0.007* (0.004)	0.001 (0.003)
R&D				0.007 (0.010)	0.021 (0.022)	0.004 (0.011)
CASH				0.001 (0.002)	0.001 (0.004)	0.002 (0.002)
Constant	0.007*** (0.000)	0.006*** (0.000)	0.007*** (0.000)	0.009*** (0.002)	0.010*** (0.003)	0.008*** (0.002)
Observations	337,298	96,172	201,537	189,912	53,381	114,025
R-squared	0.128	0.164	0.135	0.133	0.176	0.138
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered	Yes	Yes	Yes	Yes	Yes	Yes

The table reports linear regressions of stock returns with multiple fixed effects for time (date) and industry (SICCD codes) levels. Robust standard errors are clustered by firm, as reported in parentheses. The characters of *** p<0.01, ** p<0.05, * p<0.1 indicate a statistically significant level at the 1%, 5%, and 10%, respectively.

Table 3: Robustness check excluding Covid-19 period						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	RET Full sample Excluding Covid-19	RET Negative Anomaly [Abnormal Cooler] Excluding Covid-19	RET Positive Anomaly [Abnormal Warmer] Excluding Covid-19	RET Full sample Excluding Covid-19	RET Negative Anomaly [Abnormal Cooler] Excluding Covid-19	RET Positive Anomaly [Abnormal Warmer] Excluding Covid-19
SL-CCS	-0.275*** (0.036)	-2.488*** (0.071)	0.891*** (0.046)	-0.295*** (0.049)	-2.579*** (0.094)	0.846*** (0.063)
SIZE				-0.000* (0.000)	-0.000 (0.000)	-0.000 (0.000)
BM				0.000 (0.000)	-0.000 (0.001)	0.000 (0.000)
LEV				0.000 (0.001)	0.004* (0.002)	-0.001 (0.001)
Q				-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
CAPEX				0.012 (0.009)	0.017 (0.016)	0.010 (0.011)
TANG				-0.004** (0.002)	-0.007* (0.004)	-0.003 (0.002)
ROA				0.001 (0.003)	0.009 (0.006)	0.000 (0.004)
SALE				-0.002 (0.002)	-0.008** (0.004)	0.001 (0.003)
R&D				0.003 (0.010)	0.021 (0.022)	-0.002 (0.011)
CASH				0.001 (0.002)	0.001 (0.004)	0.003 (0.003)
Constant	0.007*** (0.000)	0.006*** (0.000)	0.008*** (0.000)	0.009*** (0.002)	0.009*** (0.003)	0.007*** (0.002)
Observations	309,756	91,224	181,234	177,171	51,216	104,535
R-squared	0.122	0.159	0.127	0.128	0.172	0.132
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered	Yes	Yes	Yes	Yes	Yes	Yes

The table reports linear regressions of stock returns with multiple fixed effects for time (date) and industry (SICCD codes) levels. Robust standard errors are clustered by firm, as reported in parentheses. The characters of *** p<0.01, ** p<0.05, * p<0.1 indicate a statistically significant level at the 1%, 5%, and 10%, respectively.

Table 4: Mediation tests – Polluting stocks

VARIABLES	(1) RET Full sample Excluding Covid-19	(2) RET Negative Anomaly [Abnormal Cooler] Excluding Covid-19	(3) RET Positive Anomaly [Abnormal Warmer] Excluding Covid-19
SL-CCS	-0.254*** (0.059)	-2.508*** (0.115)	0.852*** (0.075)
POLLUTING STOCKS	0.001 (0.001)	0.003 (0.002)	-0.001 (0.001)
SL-CCS x POLLUTING STOCKS	-0.139 (0.105)	-0.231 (0.201)	-0.023 (0.141)
SIZE	-0.000* (0.000)	-0.000 (0.000)	-0.000 (0.000)
BM	0.000 (0.000)	-0.000 (0.001)	0.000 (0.000)
LEV	0.000 (0.001)	0.004* (0.002)	-0.001 (0.001)
Q	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
CAPEX	0.012 (0.009)	0.016 (0.016)	0.010 (0.011)
TANG	-0.005** (0.002)	-0.008** (0.004)	-0.003 (0.003)
ROA	0.001 (0.003)	0.009 (0.006)	-0.000 (0.004)
SALE	-0.002 (0.002)	-0.008** (0.004)	0.001 (0.003)
R&D	0.004 (0.010)	0.024 (0.023)	-0.003 (0.011)
CASH	0.001 (0.002)	0.001 (0.004)	0.003 (0.003)
Constant	0.008*** (0.002)	0.009** (0.003)	0.008*** (0.002)
Observations	177,171	51,216	104,535
R-squared	0.128	0.172	0.132
Time FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
SE Clustered	Yes	Yes	Yes

The table reports linear regressions of stock returns with multiple fixed effects for time (date) and industry (SICCD codes) levels. Robust standard errors are clustered by firm, as reported in parentheses. The characters of *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ indicate a statistically significant level at the 1%, 5%, and 10%, respectively.

Table 5A: Moderation tests – Disaster-prone states [DPS]

VARIABLES	(1) RET Full sample Excluding Covid-19	(2) RET Negative Anomaly [Abnormal Cooler] Excluding Covid-19	(3) RET Positive Anomaly [Abnormal Warmer] Excluding Covid-19
SL-CCS	-0.408*** (0.069)	-2.814*** (0.134)	0.896*** (0.094)
DPS	-0.001 (0.001)	-0.004** (0.002)	0.000 (0.001)
SL-CCS x DPS	0.216** (0.097)	0.471** (0.188)	-0.094 (0.126)
SIZE	-0.000* (0.000)	-0.000 (0.000)	-0.000 (0.000)
BM	-0.000 (0.000)	-0.000 (0.001)	0.000 (0.000)
LEV	0.000 (0.001)	0.004* (0.002)	-0.001 (0.001)
Q	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
CAPEX	0.012 (0.009)	0.016 (0.016)	0.010 (0.011)
TANG	-0.005** (0.002)	-0.007* (0.004)	-0.003 (0.002)
ROA	0.001 (0.003)	0.009 (0.006)	0.000 (0.004)
SALE	-0.002 (0.002)	-0.008** (0.004)	0.001 (0.003)
R&D	0.003 (0.010)	0.021 (0.023)	-0.002 (0.011)
CASH	0.001 (0.002)	0.001 (0.004)	0.003 (0.003)
Constant	0.009*** (0.002)	0.011*** (0.003)	0.007*** (0.002)
Observations	177,171	51,216	104,535
R-squared	0.128	0.172	0.132
Time FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
SE Clustered	Yes	Yes	Yes

The table reports linear regressions of stock returns with multiple fixed effects for time (date) and industry (SICCD codes) levels. Robust standard errors are clustered by firm, as reported in parentheses. The characters of *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ indicate a statistically significant level at the 1%, 5%, and 10%, respectively.

Table 5B: Moderation tests – State-led adaptation plans finalized [SAPF]

VARIABLES	(1) RET Full sample Excluding Covid-19	(2) RET Negative Anomaly [Abnormal Cooler] Excluding Covid-19	(3) RET Positive Anomaly [Abnormal Warmer] Excluding Covid-19
SL-CCS	-0.318*** (0.050)	-2.573*** (0.098)	0.821*** (0.065)
SAPF	0.003* (0.002)	0.002 (0.003)	0.005** (0.002)
SL-CCS x SAPF	0.392* (0.201)	-0.115 (0.365)	0.414 (0.268)
SIZE	-0.000* (0.000)	-0.000 (0.000)	-0.000 (0.000)
BM	0.000 (0.000)	-0.000 (0.001)	0.000 (0.000)
LEV	0.000 (0.001)	0.004* (0.002)	-0.001 (0.001)
Q	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
CAPEX	0.012 (0.009)	0.017 (0.016)	0.009 (0.011)
TANG	-0.004* (0.002)	-0.006* (0.004)	-0.003 (0.002)
ROA	0.001 (0.003)	0.009 (0.006)	-0.000 (0.004)
SALE	-0.002 (0.002)	-0.008** (0.004)	0.001 (0.003)
R&D	0.002 (0.010)	0.021 (0.022)	-0.003 (0.011)
CASH	0.001 (0.002)	0.001 (0.004)	0.003 (0.003)
Constant	0.009*** (0.002)	0.009*** (0.003)	0.007*** (0.002)
Observations	177,171	51,216	104,535
R-squared	0.128	0.172	0.132
Time FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
SE Clustered	Yes	Yes	Yes

The table reports linear regressions of stock returns with multiple fixed effects for time (date) and industry (SICCD codes) levels. Robust standard errors are clustered by firm, as reported in parentheses. The characters of *** p<0.01, ** p<0.05, * p<0.1 indicate a statistically significant level at the 1%, 5%, and 10%, respectively.

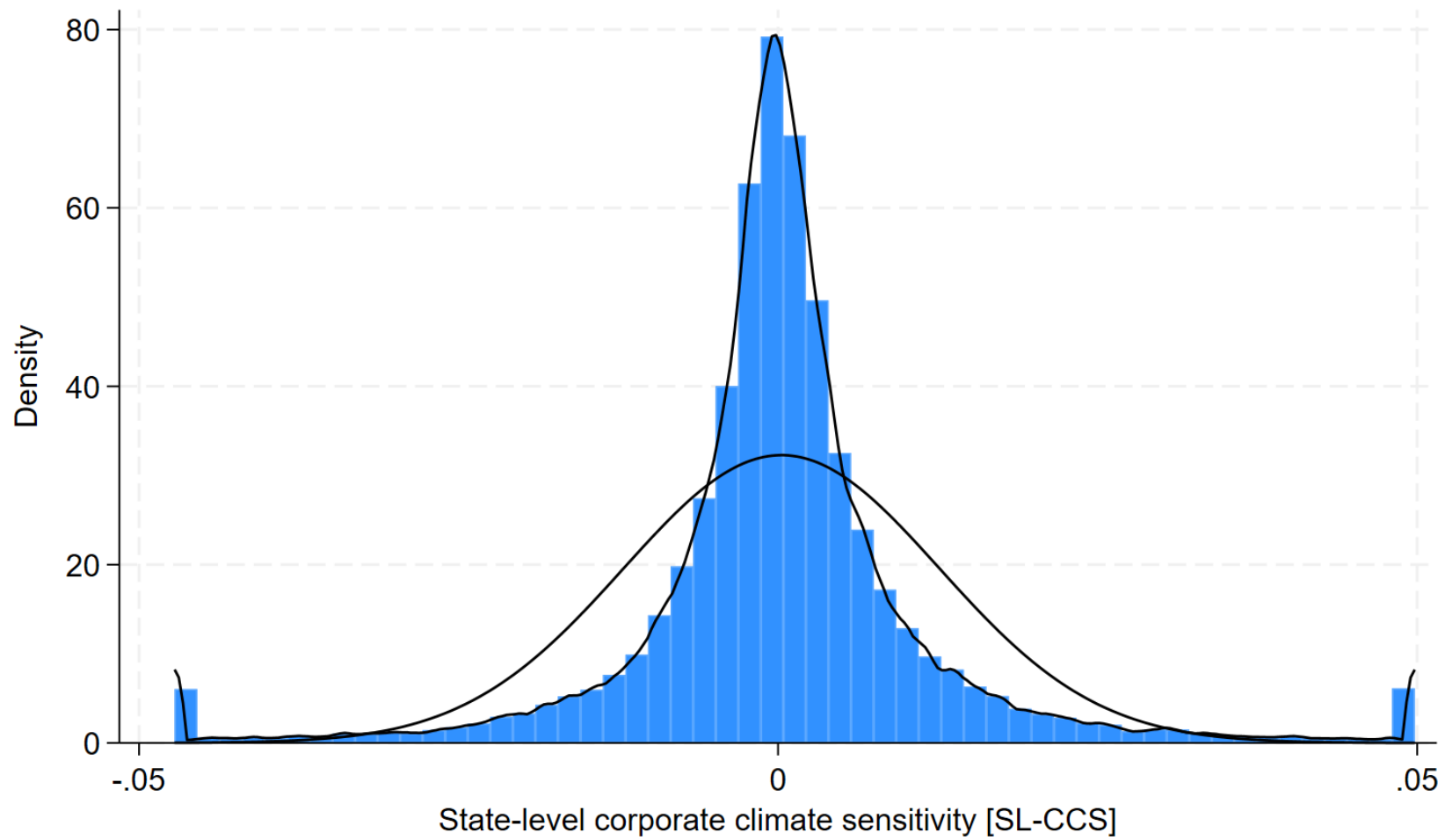


Figure 1: A histogram of the State-Level Corporate Climate Sensitivity [SL-CCS] predicted with a kernel density estimate.

Appendix A1: Variables and definitions.

Variable	Definition
RET	Monthly stock return. Source: Center for Research in Security Prices [CRSP] monthly stock file [MSF].
Ri-Rf	Monthly stock excess return is the difference between stock return [RET] and risk-free rate [Rf] using a 3-Month Treasury Bill Secondary Market Rate, Discount Basis (TB3MS). Source: Center for Research in Security Prices [CRSP] monthly stock file [MSF], FRED, and author's calculation.
SL-CCS	Monthly state-level corporate climate sensitivity, indicating a firm's sensitivity to monthly state-level temperature anomaly. The predicted SL-CCS beta captures the sensitivity of a firm's stock to state-level and long-term climate factors with negative or positive temperature anomaly values. Source: Author's calculation using Equation 1 with data archives extracted from Center for Research in Security Prices [CRSP], NOAA's National Centers for Environmental Information (NCEI), and FRED.
SLTA	Monthly state-level temperature anomaly. For each US state, SLTA is calculated as the difference between the current temperature value and its 30-year average or more benchmark temperature value. A positive value of SLTA indicates that the temperature is abnormally warmer than normal. A negative value of SLTA indicates that the temperature is abnormally cooler than normal. Source: raw data archives are extracted from NOAA's National Centers for Environmental Information (NCEI).
SIZE	Firm size is measured by the logarithm value of one plus a firm's assets total [ATQ]. Source: COMPUSTAT Quarterly and author's calculation.
BM	book-to-market value. The market value of equity (ME) is the product of Price Close – Quarter [PRCCQ] multiplied by Common Shares Outstanding [CSHOQ]. Book value (BM) is calculated as the product of assets total [ATQ], divided by the sum of market value of equity (ME) plus Debt in Current Liabilities [DLCQ] and Long-Term Debt – Total [DLTTQ]. Source: COMPUSTAT Quarterly and author's calculation.
LEV	The financial leverage ratio is calculated as the product of Debt in Current Liabilities [DLCQ] plus Long-Term Debt – Total [DLTTQ], divided by assets total quarterly [ATQ]. Source: COMPUSTAT Quarterly and author's calculation.
Q	Tobin's Q ratio is calculated as the product of assets total [ATQ], plus the market value of equity [ME] minus Common/Ordinary Equity – Total [CEQQ], divided by assets total. Source: COMPUSTAT Quarterly and author's calculation.
CAPEX	Capital expenditure [CAPXY] to assets total [ATQ]. Source: COMPUSTAT Quarterly and author's calculation.
TANG	Corporate tangibility is calculated as the fraction of Property Plant and Equipment - Total (Net) [PPENTQ] divided by assets total [ATQ]. Source: COMPUSTAT Quarterly and author's calculation.
ROA	corporate return on assets. ROA is the product of Net Income (Loss) [NIQ], Depreciation and Amortization – Total [DPQ], Income Taxes – Total [TXTQ], and Interest and Related Expenses- Total [XINTQ], divided by assets total quarterly [ATQ]. Source: COMPUSTAT Quarterly and author's calculation.
SALE	A firm' sales calculated as the fraction of revenue [REVTQ] to assets total [ATQ]. Source: COMPUSTAT Quarterly and author's calculation.
R&D	Corporate Research and Development Expense [XRDQ] to assets total [ATQ]. Source: COMPUSTAT Quarterly and author's calculation.

CASH	Corporate cash holdings are calculated as the fraction of Cash and Short-Term Investments [CHEQ] divided by assets total [ATQ]. Source: COMPUSTAT Quarterly and author's calculation.
POLLUT ING STOCKS	A dummy variable that is set equal to one for firms' stocks that belong to polluting industries. The polluting industries include Energy [GSECTOR=10], Materials [GSECTOR=15], Industrials [GSECTOR=20], and Utilities [GSECTOR=55], otherwise set equal to zero. Source: COMPUSTAT Quarterly and author's calculation.
SAPF	A dummy variable set equal to one for US states with state-led plans finalized for their local/state climate action, otherwise set equal to zero. SAPF captures climate transitional risk in the US states. Source: State and Local Adaptation Plans - Georgetown Climate Center and author's calculation.
DPS	A dummy variable set equal to one for disaster-prone states, otherwise set equal to zero. Source: The Most Disaster-Prone States in the U.S. and author's calculation.

Note: Data subscriptions of stock prices [CRSP] and COMPUSTAT within Wharton Research Data Services (WRDS) are accessed using a licensed account by the corresponding sole author having all the rights reserved for the used datasets.

Appendix A2: Descriptive statistics [excluding Covid-19 period]						
Variable	N	Mean	Min	p50	Max	SD
RET	327184	0.007	-0.441	0.000	0.660	0.169
Ri-Rf	327184	-3.384	-8.213	-3.803	0.208	2.332
SL-CCS	312794	0.000	-0.047	0.000	0.050	0.012
SLTA	322650	1.203	-16.000	1.000	18.000	3.310
SIZE	265614	4.861	0.054	4.826	11.005	2.493
BM	215595	1.343	0.014	0.901	9.092	1.551
LEV	247459	0.309	0.000	0.186	4.104	0.522
Q	228706	2.982	0.455	1.365	51.796	6.301
CAPEX	239243	0.035	0.000	0.015	0.343	0.058
TANG	256471	0.261	0.000	0.160	0.950	0.269
ROA	258455	-0.040	-1.575	0.008	0.131	0.209
SALE	262022	0.222	0.000	0.162	1.160	0.231
R&D	332130	0.012	0.000	0.000	0.510	0.044
CASH	262405	0.175	0.000	0.067	0.974	0.236

Appendix A3: Descriptive statistics [excluding Covid-19 period and penny stocks]						
Variable	N	Mean	Min	p50	Max	SD
RET	288141	0.012	-0.441	0.001	0.660	0.161
Ri-Rf	288141	-3.254	-8.213	-3.608	0.208	2.287
SL-CCS	276101	0.000	-0.047	0.000	0.050	0.011
SLTA	284195	1.230	-16.000	1.000	18.000	3.320
SIZE	233447	4.879	0.054	4.864	11.005	2.492
BM	190301	1.344	0.014	0.895	9.092	1.559
LEV	217735	0.308	0.000	0.181	4.104	0.525
Q	201633	2.998	0.455	1.375	51.796	6.283
CAPEX	210801	0.035	0.000	0.015	0.343	0.058
TANG	225187	0.260	0.000	0.158	0.950	0.270
ROA	227066	-0.040	-1.575	0.008	0.131	0.209
SALE	230230	0.219	0.000	0.158	1.160	0.228
R&D	292853	0.012	0.000	0.000	0.510	0.044
CASH	230664	0.178	0.000	0.068	0.974	0.238

Appendix A4: Descriptive statistics by temperature anomaly levels

	Negative Anomaly [Abnormal Cooler]	Positive Anomaly [Abnormal Warmer]	Total
N	141,601 (39.1%)	220,653 (60.9%)	362,254 (100.0%)
RET	0.005 (0.168)	0.008 (0.170)	0.007 (0.170)
Ri-Rf	-3.418 (2.365)	-3.034 (2.353)	-3.184 (2.365)
SL-CCS	0.000 (0.012)	0.000 (0.013)	0.000 (0.012)
SLTA	-1.783 (1.961)	3.376 (2.282)	1.303 (3.326)
SIZE	4.858 (2.496)	4.979 (2.537)	4.931 (2.521)
BM	1.360 (1.556)	1.345 (1.586)	1.351 (1.574)
LEV	0.306 (0.512)	0.315 (0.538)	0.311 (0.528)
Q	2.849 (5.994)	3.107 (6.563)	3.006 (6.347)
CAPEX	0.036 (0.058)	0.033 (0.056)	0.034 (0.057)
TANG	0.263 (0.267)	0.257 (0.272)	0.259 (0.270)
ROA	-0.036 (0.203)	-0.044 (0.214)	-0.041 (0.210)
SALE	0.226 (0.232)	0.210 (0.226)	0.216 (0.228)
R&D	0.011 (0.042)	0.012 (0.045)	0.011 (0.044)
CASH	0.172 (0.233)	0.186 (0.246)	0.181 (0.241)

Appendix A5: Descriptive statistics by disaster-prone states [DPS]			
	Non-DPS	DPS	Total
N	218,119 (60.2%)	144,135 (39.8%)	362,254 (100.0%)
RET	0.007 (0.168)	0.007 (0.171)	0.007 (0.170)
Ri-Rf	-3.113 (2.348)	-3.293 (2.386)	-3.184 (2.365)
SL-CCS	0.001 (0.012)	-0.000 (0.013)	0.000 (0.012)
SLTA	1.280 (3.546)	1.336 (2.978)	1.303 (3.326)
SIZE	5.112 (2.456)	4.637 (2.598)	4.931 (2.521)
BM	1.434 (1.635)	1.217 (1.463)	1.351 (1.574)
LEV	0.302 (0.511)	0.327 (0.554)	0.311 (0.528)
Q	2.756 (5.794)	3.400 (7.115)	3.006 (6.347)
CAPEX	0.036 (0.059)	0.031 (0.053)	0.034 (0.057)
TANG	0.286 (0.282)	0.215 (0.243)	0.259 (0.270)
ROA	-0.032 (0.195)	-0.055 (0.231)	-0.041 (0.210)
SALE	0.211 (0.224)	0.224 (0.236)	0.216 (0.228)
R&D	0.010 (0.042)	0.014 (0.047)	0.011 (0.044)
CASH	0.163 (0.232)	0.209 (0.252)	0.181 (0.241)

Appendix A6: Descriptive statistics by state-led adaptation plans finalized [SAPF]			
	Non SAPF	SAPF	Total
N	313,350 (86.5%)	48,904 (13.5%)	362,254 (100.0%)
RET	0.007 (0.171)	0.007 (0.157)	0.007 (0.170)
Ri-Rf	-3.575 (2.276)	-0.691 (1.029)	-3.184 (2.365)
SL-CCS	0.000 (0.012)	-0.001 (0.012)	0.000 (0.012)
SLTA	1.187 (3.341)	2.022 (3.136)	1.303 (3.326)
SIZE	4.843 (2.492)	5.728 (2.645)	4.931 (2.521)
BM	1.355 (1.552)	1.309 (1.759)	1.351 (1.574)
LEV	0.304 (0.504)	0.383 (0.713)	0.311 (0.528)
Q	2.862 (5.984)	4.229 (8.765)	3.006 (6.347)
CAPEX	0.036 (0.058)	0.018 (0.042)	0.034 (0.057)
TANG	0.270 (0.272)	0.155 (0.222)	0.259 (0.270)
ROA	-0.036 (0.200)	-0.082 (0.283)	-0.041 (0.210)
SALE	0.222 (0.230)	0.162 (0.211)	0.216 (0.228)
R&D	0.011 (0.042)	0.016 (0.054)	0.011 (0.044)
CASH	0.172 (0.233)	0.259 (0.289)	0.181 (0.241)

Appendix A7: State-level corporate climate sensitivity [SL-CCS] and stock returns [RET] excluding penny stocks and the Covid-19 period

VARIABLES	(1) RET Full sample	(2) RET Negative Anomaly [Abnormal Cooler]	(3) RET Positive Anomaly [Abnormal Warmer]	(4) RET Full sample	(5) RET Negative Anomaly [Abnormal Cooler]	(6) RET Positive Anomaly [Abnormal Warmer]
SL-CCS	-0.246*** (0.037)	-2.439*** (0.076)	0.889*** (0.047)	- 0.266*** (0.050)	-2.479*** (0.101)	0.833*** (0.064)
SIZE				-0.000* (0.000)	-0.000 (0.000)	0.000 (0.000)
BM				0.000 (0.000)	0.000 (0.001)	0.000 (0.000)
LEV				0.000 (0.001)	0.004* (0.002)	-0.001 (0.001)
Q				-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)
CAPEX				0.009 (0.008)	0.005 (0.016)	0.010 (0.011)
TANG				- 0.005*** (0.002)	-0.007* (0.004)	-0.004* (0.002)
ROA				0.001 (0.003)	0.010* (0.006)	-0.001 (0.004)
SALE				-0.003 (0.002)	-0.010** (0.004)	0.002 (0.003)
R&D				0.002 (0.010)	0.023 (0.023)	-0.004 (0.011)
CASH				0.000 (0.002)	-0.001 (0.004)	0.004 (0.003)
Constant	0.012*** (0.000)	0.011*** (0.000)	0.013*** (0.000)	0.014*** (0.002)	0.015*** (0.003)	0.012*** (0.002)
Observations	274,045	80,261	161,307	157,273	45,189	93,337
R-squared	0.133	0.165	0.140	0.137	0.176	0.142
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered	Yes	Yes	Yes	Yes	Yes	Yes

The table reports linear regressions of stock returns with multiple fixed effects for time (date) and industry (SICCD codes) levels. Robust standard errors are clustered by firm, as reported in parentheses. The characters of *** p<0.01, ** p<0.05, * p<0.1 indicate a statistically significant level at the 1%, 5%, and 10%, respectively.

Appendix A8: Mediation tests – Polluting stocks excluding penny stocks and the Covid-19 period

VARIABLES	(1) RET Full sample Excluding Covid-19	(2) RET Negative Anomaly [Abnormal Cooler] Excluding Covid-19	(3) RET Positive Anomaly [Abnormal Warmer] Excluding Covid-19
SL-CCS	-0.206*** (0.060)	-2.426*** (0.124)	0.852*** (0.074)
POLLUTING STOCKS	0.001 (0.001)	0.003* (0.002)	-0.002 (0.001)
SL-CCS x POLLUTING STOCKS	-0.208* (0.107)	-0.174 (0.212)	-0.066 (0.151)
SIZE	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
BM	0.000 (0.000)	0.000 (0.001)	0.000 (0.000)
LEV	0.000 (0.001)	0.004** (0.002)	-0.001 (0.001)
Q	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)
CAPEX	0.009 (0.008)	0.005 (0.016)	0.010 (0.011)
TANG	-0.006*** (0.002)	-0.009** (0.004)	-0.003 (0.002)
ROA	0.001 (0.003)	0.010* (0.006)	-0.001 (0.004)
SALE	-0.002 (0.002)	-0.010** (0.004)	0.002 (0.003)
R&D	0.003 (0.010)	0.027 (0.023)	-0.007 (0.011)
CASH	0.000 (0.002)	-0.001 (0.004)	0.004 (0.003)
Constant	0.014*** (0.002)	0.014*** (0.003)	0.012*** (0.002)
Observations	157,273	45,189	93,337
R-squared	0.137	0.177	0.142
Time FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
SE Clustered	Yes	Yes	Yes

The table reports linear regressions of stock returns with multiple fixed effects for time (date) and industry (SICCD codes) levels. Robust standard errors are clustered by firm, as reported in parentheses. The characters of *** p<0.01, ** p<0.05, * p<0.1 indicate a statistically significant level at the 1%, 5%, and 10%, respectively.

Appendix A9: Moderation tests – Disaster-prone states [DPS] excluding penny stocks and the Covid-19 period

VARIABLES	(1) RET Full sample Excluding Covid-19	(2) RET Negative Anomaly [Abnormal Cooler] Excluding Covid-19	(3) RET Positive Anomaly [Abnormal Warmer] Excluding Covid- 19
SL-CCS	-0.347*** (0.070)	-2.610*** (0.143)	0.905*** (0.093)
DPS	-0.001 (0.001)	-0.004** (0.002)	0.000 (0.001)
SL-CCS x DPS	0.158 (0.100)	0.261 (0.203)	-0.136 (0.128)
SIZE	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)
BM	-0.000 (0.000)	0.000 (0.001)	0.000 (0.000)
LEV	0.000 (0.001)	0.004* (0.002)	-0.001 (0.001)
Q	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)
CAPEX	0.009 (0.008)	0.004 (0.016)	0.010 (0.011)
TANG	-0.006*** (0.002)	-0.007* (0.004)	-0.004* (0.002)
ROA	0.001 (0.003)	0.009 (0.006)	-0.001 (0.004)
SALE	-0.003 (0.002)	-0.010** (0.004)	0.002 (0.003)
R&D	0.002 (0.010)	0.023 (0.023)	-0.004 (0.011)
CASH	0.000 (0.002)	-0.001 (0.004)	0.004 (0.003)
Constant	0.015*** (0.002)	0.017*** (0.003)	0.011*** (0.002)
Observations	157,273	45,189	93,337
R-squared	0.137	0.177	0.142
Time FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
SE Clustered	Yes	Yes	Yes

The table reports linear regressions of stock returns with multiple fixed effects for time (date) and industry (SICCD codes) levels. Robust standard errors are clustered by firm, as reported in parentheses. The characters of *** p<0.01, ** p<0.05, * p<0.1 indicate a statistically significant level at the 1%, 5%, and 10%, respectively.

Appendix A10: Moderation tests – State-led adaptation plans finalized [SAPF] excluding penny stocks and the Covid-19 period

	(1)	(2)	(3)
VARIABLES	RET Full sample Excluding Covid-19	RET Negative Anomaly [Abnormal Cooler] Excluding Covid-19	RET Positive Anomaly [Abnormal Warmer] Excluding Covid- 19
SL-CCS	-0.277*** (0.051)	-2.478*** (0.104)	0.823*** (0.067)
SAPF	0.003** (0.001)	0.002 (0.003)	0.004** (0.002)
SL-CCS x SAPF	0.197 (0.221)	-0.036 (0.451)	0.167 (0.251)
SIZE	-0.000* (0.000)	-0.000 (0.000)	-0.000 (0.000)
BM	0.000 (0.000)	0.000 (0.001)	0.000 (0.000)
LEV	0.000 (0.001)	0.004* (0.002)	-0.001 (0.001)
Q	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
CAPEX	0.009 (0.008)	0.005 (0.016)	0.009 (0.011)
TANG	-0.005*** (0.002)	-0.007* (0.004)	-0.004 (0.002)
ROA	0.001 (0.003)	0.010* (0.006)	-0.001 (0.004)
SALE	-0.003 (0.002)	-0.010** (0.004)	0.002 (0.003)
R&D	0.001 (0.010)	0.023 (0.023)	-0.005 (0.011)
CASH	0.000 (0.002)	-0.001 (0.004)	0.004 (0.003)
Constant	0.014*** (0.002)	0.015*** (0.003)	0.011*** (0.002)
Observations	157,273	45,189	93,337
R-squared	0.137	0.176	0.142
Time FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
SE Clustered	Yes	Yes	Yes

The table reports linear regressions of stock returns with multiple fixed effects for time (date) and industry (SICCD codes) levels. Robust standard errors are clustered by firm, as reported in parentheses. The characters of *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ indicate a statistically significant level at the 1%, 5%, and 10%, respectively.

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