Climate Disaster Risk and Stock Returns *

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Abstract

This paper investigates whether climate disaster risk is priced in the cross-section of U.S. stock returns. I construct national and state-level climate disaster indices for the Contiguous United States based on the physical strength of acute climate hazards (storms, floods, droughts, and heatwaves). These indices are used to estimate stock return covariance with physical climate risk, which leads to finding that safer stocks, those with a higher climate disaster beta, earn lower future returns. In particular, this negative relation between climate disaster beta and future returns becomes more pronounced following times of heightened disaster risk. This paper further shows that geographically dispersed business operations and high cash holdings pay off when the market is concerned about climate change risk. These findings are consistent with the risk-return tradeoff and the asset pricing implications of demand for stocks with high potential to hedge against climate risk.

Keywords: climate change, climate disaster risk, climate finance, asset pricing;

JEL classification: G11, G12, Q54

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1 Introduction

Climate change can impact all areas of human life, including economic activity through material impacts on households, corporations, and markets.[1] The consequences of climate change now include, among others, intense droughts, water scarcity, severe fires, rising sea levels, flooding, melting polar ice, catastrophic storms and declining biodiversity (IPCC (2022)). As a result of extreme weather events of higher frequency and magnitude, market participants have tried to integrate climate risks into their investment process, which requires reliable estimates of physical climate risk and firm-level exposure to it[2].

In this study, I investigate whether climate change, as a driver of disaster risk, is priced in the cross-section of U.S. stock returns. First, monthly climate disaster risk indices are constructed. These are based on the physical strength of acute climate hazards (storms, floods, droughts, and heatwaves) in the Contiguous United States, both at the national and state-level. Next, I measure a stock's sensitivity to climate disasters, denoted β^{CLD} (climate disaster beta), by estimating the stock return's covariance with the physical climate risk index. Specifically, the baseline β^{CLD} is estimated from 60-month rolling regressions of stock excess returns on the monthly state-level climate disaster index of the firm's headquarters. By construction, a higher β^{CLD} indicates higher stock returns as the climate disaster index increases. In other words, a higher β^{CLD} signals more resilience (lower risk) to climate disasters, whereas a lower β^{CLD} signals more vulnerability (higher risk). Examining the performance of the monthly β^{CLD} in predicting cross-sectional variations in future stock returns, I find that the risk-return tradeoff is present, that is, stocks with a higher β^{CLD} are significantly associated with lower future returns. A one-standard-deviation increase in climate disaster betas is associated with a decrease in future excess returns of 4.95 basis points (bps) per month, representing a 4.51% reduction relative to the sample mean.

I conduct another exercise to test a time-varying premium hypothesis. During times of heightened climate disaster risk, a one-standard-deviation increase in the climate disaster beta

[1] Weather-related events such as storms, floods, droughts, and wildfires caused global annual economic losses of USD 212bn on average over the last decade (Swiss Re Institute (2020)).

[2] Climate change risks are divided into physical and transition. Physical risk, associated with physical damages to assets, could also be of two sorts: acute (e.g. droughts, floods, storms, heatwaves), or chronic, related to long term climate shifts (e.g. sea level rise and changes in weather patterns). Transition risk include, among other components, policy risks which emerge from potential introduction of more stringent environmental policies that can affect the return of brown assets.

is associated with a total reduction of 9.29% in future monthly stock returns relative to the sample mean. This finding is consistent with the prediction that any cross-sectional differences in returns associated with climate disasters, if it exists, should be higher when a disaster occurs (Chen, Joslin, and Tran (2012)). One may also interpret this result as follows, when risk aversion increases during times of heightened climate risk, investors' intertemporal hedging demand is expected to become more pronounced. Thus, these investors are willing to accept even lower future returns from stocks with a higher β^{CLD} for hedging purposes in times of high climate disaster index.

Next, I explore whether organizational structure and corporate policies matter for determining a firm's vulnerability to climate disasters. Using two alternate measures of geographical dispersion, this paper finds that β^{CLD} is positively associated with a firm's geographical dispersion when local climate disaster risk is high. Intuitively, geographically dispersed firms have stronger economic interests outside their headquarters state, are more diversified and thus relatively less affected by local risk factors than geographically focused firms are. In a similar vein, during times of intensified climate disaster risk, β^{CLD} is significantly higher among firms with larger cash holdings. This is consistent with the idea of firms hoarding cash for precautionary motive in order to mitigate risks they cannot hedge. Taken together, investors perceive firms that either diversify their operations geographically or hold large amounts of cash as less risky when climate disaster risk is high.

Overall, these findings are consistent with the rare-disaster literature (see, for example, Rietz (1988), Barro (2006), and Gabaix (2012)), which posits that the value loss suffered by assets in a disaster varies both in the cross-section and over time. In particular, when agents are optimistic about stocks (and think they will do reasonably well during disasters), stock premia are low, stock valuations are high, and future returns are low. However, this optimism about resilience to disasters may change over time. This yields a time-varying risk premium. Gabaix (2012) presents the model as rational, but it can be also viewed as a tractable way to model less orthodox things, such as "time-varying perception of risk," or "investor sentiment."

The novel indices constructed in this study help informing policymakers, investors, and the general public about the changing climate and some of its potential impacts on the United States. They are also likely to be useful in other applications than the one of this paper, especially those in need of disaggregated data at the state level. For instance, an index that has been used in the economics literature (e.g., Kim, Matthes, and Phan (2022), Liao, Sheng, Gupta, and Karmakar (2024)) is the Actuaries Climate Index (ACI). It is developed by actuary associations of Canada and the U.S. to provide an aggregate indicator of the frequency of severe weather. However, the ACI is only available for seven regions of the U.S.[3], not at the state level.

In addition, this paper contributes to the growing climate finance literature that examines the effect of climate change risk on financial markets and firms (e.g., Engle, Giglio, Kelly, Lee, and Stroebel (2020); Ilhan, Sautner, and Vilkov (2021); Pástor, Stambaugh, and Taylor (2022); Sautner, Van Lent, Vilkov, and Zhang (2023)). While Hong, Li, and Xu (2019) and Faccini, Matin, and Skiadopoulos (2023) do not find physical climate risk to be yet priced in U.S. stocks, others studies do. Choi, Gao, and Jiang (2020) find that stocks of carbon-intensive firms underperform firms with low-carbon emissions in abnormally warm weather. Bansal, Kiku, and Ochoa (2019) show that global warming carries a positive risk premium that increases with the level of temperature. Huynh, Nguyen, and Truong (2020) offer evidence of a significant positive relation between drought risk and the cost of equity capital. Alok, Kumar, and Wermers (2020) document that professional money managers overreact to large climate disasters, especially salient ones like hurricanes and tornadoes.

This study differs from existing work in both its theoretical and empirical contributions. Theoretically, the motivation is the rare-disaster literature to examine the effect of climate disaster risk on stock returns. Empirically, the measure of stock exposure to climate disaster risk, β^{CLD}, is distinct from other measures explored in the literature. Here, exposure to climate disasters can be recovered for any assets which returns are observed. For instance, Sautner et al. (2023) and Li, Shan, Tang, and Yao (2024) alternatively construct measures of firm-level exposure to climate risk based on quarterly earnings call transcripts. However, measures of physical climate risk exposure are far more sparse than transition risk exposure. Thus, their measure of physical risk exposure is either zero or close to zero for most observations. Consequently, they do not obtain sufficient variation across stocks. Additionally, our estimation procedure does not directly rely on the voluntary disclosure of firm-level information, such as

[3]Alaska, Central East Atlantic, Central West Pacific, Midwest, Southeast Atlantic, Southern Plains, and Southwest Pacific.

Gostlow (2021) and Acharya, Johnson, Sundaresan, and Tomunen (2022)[4]. Moreover, due to the market-based nature of our measure, climate disaster betas could potentially reflect market participants' risk perceptions and expectations. In that respect, climate disaster betas allow a clear distinction between vulnerable assets that are expected to underperform and resilient assets that are expected to do well in a climate disaster.

By investigating the effect of stock exposure to climate disaster risk on future returns, this study offers a direct response to the call of Giglio, Kelly, and Stroebel (2021) for research on this important yet unexplored question. These authors invite future research to improve on current measures of climate risk exposure in equity assets. This study also contributes to the literature examining the cross-sectional determinants of stock returns by showing that climate disaster risk is a novel factor affecting stocks' future returns. This paper further relates to the Securities and Exchange Commission's (SEC) efforts to respond to investors' demand for more consistent, comparable, and reliable information about the financial effects of climate-related risks on a registrant's operations. Particularly, in March 2024, the SEC approved a landmark rule requiring U.S.-listed companies to communicate how they are managing material risks related to climate change and how those risks affect their bottom lines[5].

The remainder of the paper is organized as follows. Section 2 introduces the hypotheses. Section 3 describes the data sources and variables used in the tests. Section 4 presents the empirical evidence. Section 5 carries out robustness tests. Section 6 concludes.

2 Hypotheses Development

This study investigates whether climate disaster risk is priced in the cross-section of stock returns. The empirical test is motivated by the rare-disaster literature who predicts that the equity premium is a compensation for the risk of rare, but disastrous, events such as wars, depressions, financial crises, and natural disasters (for example, Rietz (1988); Barro (2006); Manela and Moreira (2017)). In particular, Gabaix (2012) shows that the value loss suffered by assets in a disaster varies both in the cross-section and over time. When the asset is expected to do well in a disaster, investors are optimistic about the asset. In the cross-section, an asset with

[4]These papers rely on a measure of firm-level exposure to physical climate risk from a private provider named *Four Twenty Seven*, an affiliate of Moody's.

[5]https://www.sec.gov/news/press-release/2024-31

higher resilience to disasters is safer. Intuitively, more resilient stocks have a higher price, and a lower future return. Our first hypothesis is related to this literature because climate change is a driver of disaster risk as it leads to more frequent and extreme weather events. In other words, climate change increases risk for vulnerable assets; these assets may suffer supply chain disruptions or earn lower profits due to operational issues caused by severe weather events (Hsu, Lee, Peng, and Yi (2018)). Investors dislike such events because it lowers their total wealth. Therefore, they expect to be compensated with greater future returns if they hold assets that are vulnerable to physical climate risk. Conversely, they accept lower future returns from assets that are resilient to disaster risk.

To test this first prediction, I estimate monthly rolling window regressions of individual stock returns on the state-level climate disaster index of their headquarters. The monthly coefficient on the climate disaster index from these rolling regressions, denoted β^{CLD}, represents a stock return's covariance with the index. Since stocks with high β^{CLD} provide higher returns as climate disaster risk increases, they serve as resilient assets to hedge against physical climate risk. Therefore, investors would be willing to pay higher prices and accept lower future returns on stocks with a higher β^{CLD}.

Hypothesis 1. *There is a negative relation between a stock's β^{CLD} and future returns.*

The second hypothesis is based on the theoretical model of Chen et al. (2012). The authors show that, as long as there is a small amount of disagreement among investors regarding the potential disaster impact and the distribution of disaster size and intensity, the disaster risk premium should be low during normal times due to risk sharing offered by optimistic investors. However, following a disaster event, the risk premium will increase substantially because the disaster affects the consumption and wealth of these optimistic investors, causing their beliefs about disasters to converge toward those of pessimists. Therefore, any cross-sectional differences in returns associated with climate disasters, if it exists, should be higher following a disaster.

Hypothesis 2. *The negative relation between a stock's β^{CLD} and future returns is stronger in times of heightened physical climate risk.*

The previous hypotheses suggest that firms with high β^{CLD} are less vulnerable to physical climate risk. An interesting follow-up question is why investors prefer these stocks when physical climate risk is high. I investigate whether organizational structure and corporate policies matter for determining a firm's vulnerability to climate disasters. In this context, a relevant characteristic is a firm's geographical dispersion. Garcia and Norli (2012) show that, since geographically dispersed firms have stronger economic interests outside their headquarters state, they are more diversified and thus relatively less affected by local risk factors than geographically focused firms are. Another relevant characteristic is a firm's cash holdings. Bates, Kahle, and Stulz (2009) show that the significant increase in the cash holdings of U.S. firms over time is consistent with the notion that the demand for cash is to mitigate many risks that firms cannot effectively hedge. Other studies documenting that firms can mitigate physical climate risks by geographically diversifying their business segments or hoarding cash include those of Huynh et al. (2020), and Zhang and Zhu (2021). I therefore investigate whether geographic dispersion and cash holdings are useful for firms to mitigate the impact of climate disasters, and thus, to provide investors with strong hedging potential, especially when physical climate risk is high.

Hypothesis 3. *In times of high physical climate risk, a stock is more resilient (β^{CLD} is higher) when the firm is geographically dispersed or has larger cash holdings.*

3 Data and variable construction

3.1 Climate disasters

3.1.1 Storms

I use two primary data sources for wind speed: the *Storm Events Database* (SED) and the *Hurricane Databases* (HURDAT2). The SED is provided by the *National Centers for Environmental Information of the National Oceanic and Atmospheric Administration* (NOAA). It contains detailed information regarding the occurrence of storms and other significant weather phenomena having sufficient intensity to cause loss of life, injuries, significant property damage, and/or disruption to commerce; rare, unusual, weather phenomena that generate media attention; other significant meteorological events, such as record maximum or minimum temperatures, or precipitation that occur in connection with another event. To further capture tropical cyclones[6] that have made landfall in the Contiguous United States, the HURDAT2 by

[6] Tropical cyclones include depressions, storms and hurricanes.

the *National Hurricane Center* (NHC) is utilized. It contains comprehensive information on each tropical cyclone, including synoptic history, meteorological statistics, casualties and damages, and the post-analysis best track (six-hourly positions and intensities) that have occurred within the Atlantic Ocean and the Eastern Pacific Ocean[7]. Combining both datasets, I obtain a measure that brings together wind speed from SED and HURDAT2. I use the percentage difference between the maximum wind speed in knots in one month and the average maximum wind speed in the same calendar month over the last 10 years as the disaster intensity measure for storms.

3.1.2 Floods and Droughts

Precipitation data come from the NOAA's *U.S. Climate Divisional Dataset* which include records of drought, temperature, precipitation, and heating/cooling degree day values from 344 climate divisions in the Contiguous United States (CONUS). For each climate division, monthly station temperature and precipitation values are computed from the daily observations. The divisional values are weighted by area to compute state-wide, regional, and national values. Total monthly precipitation data are provided in inches. The principal measure of weather variation is the difference in monthly rainfall in inches, which is defined as the proportional deviation of total monthly rainfall from average monthly rainfall in the same calendar month over the last 10 years. This study distinguishes two disaster types, floods and droughts. Flooding events are measured by the positive difference in total monthly precipitation.

However, droughts are different since a single dry month usually does not cause a drought, but several months in a row or within a year might do so (Felbermayr and Gröschl (2014)). For this reason, I use the Palmer Z-Index, which is designed to be responsive on a monthly frequency. Negative values of -4 indicate extreme drought, values between -1 to 1 indicate regular conditions, and values of +4 indicate unusually wet periods. Similar to Huij, Laurs, Stork, and Zwinkels (2022), I create an indicator variable for droughts, which takes the value of unity if the Palmer Z-Index is below -2, which indicates moderate drought conditions.

[7]The Atlantic hurricane season is June 1st to November 30th. In the East Pacific, it runs from May 15th to November 30th.

3.1.3 Heat waves

Temperature data also come from NOAA's *U.S. Climate Divisional Dataset*. The disaster intensity measure for temperature extremes is the percentage difference between the U.S. maximum temperature in degrees Fahrenheit[8] in one month and its average in the same calendar month over the last 10 years. Strong positive deviations are interpreted as heat waves. Strong negative ones as cold waves.

3.2 Climate Disaster Index

Similar to Felbermayr and Gröschl (2014), I aggregate the different disasters into an overall climate disaster index. Like them, I work with the weighted sum of disaster intensity measures, using the inverse of the standard deviation of a disaster type over all years as precision weights. This approach makes sure that no single disaster component dominates the movement of the disaster index. I construct a national index (CLD_t) and 48 state-level indices ($CLD_{s,t}$ where $s = 1, 2, ..., 48$) for the states in the Contiguous United States. For the baseline specifications, I consider exposure to climate disasters at the state level, proxied by firms' headquarters[9]. Chaney, Sraer, and Thesmar (2012) find that headquarters and firms' major production plants tend to cluster in the same state, suggesting that a firm's headquarter location is a reasonable proxy for the location of its business operations. In particular, state-level indices can better identify the effects of local weather shocks on the local economy. Also, people are likely to focus on attention-grabbing weather events and personal experiences due to limited attention (Kahneman (1973)). The impact of disasters can also be amplified through communication channels and the media. Extreme weather events therefore serve as "wake-up calls" that alert investors to climate change (Choi et al. (2020)). I employ the national index to provide robustness to the main results. It can better capture general equilibrium and spillover effects, that is, asset prices

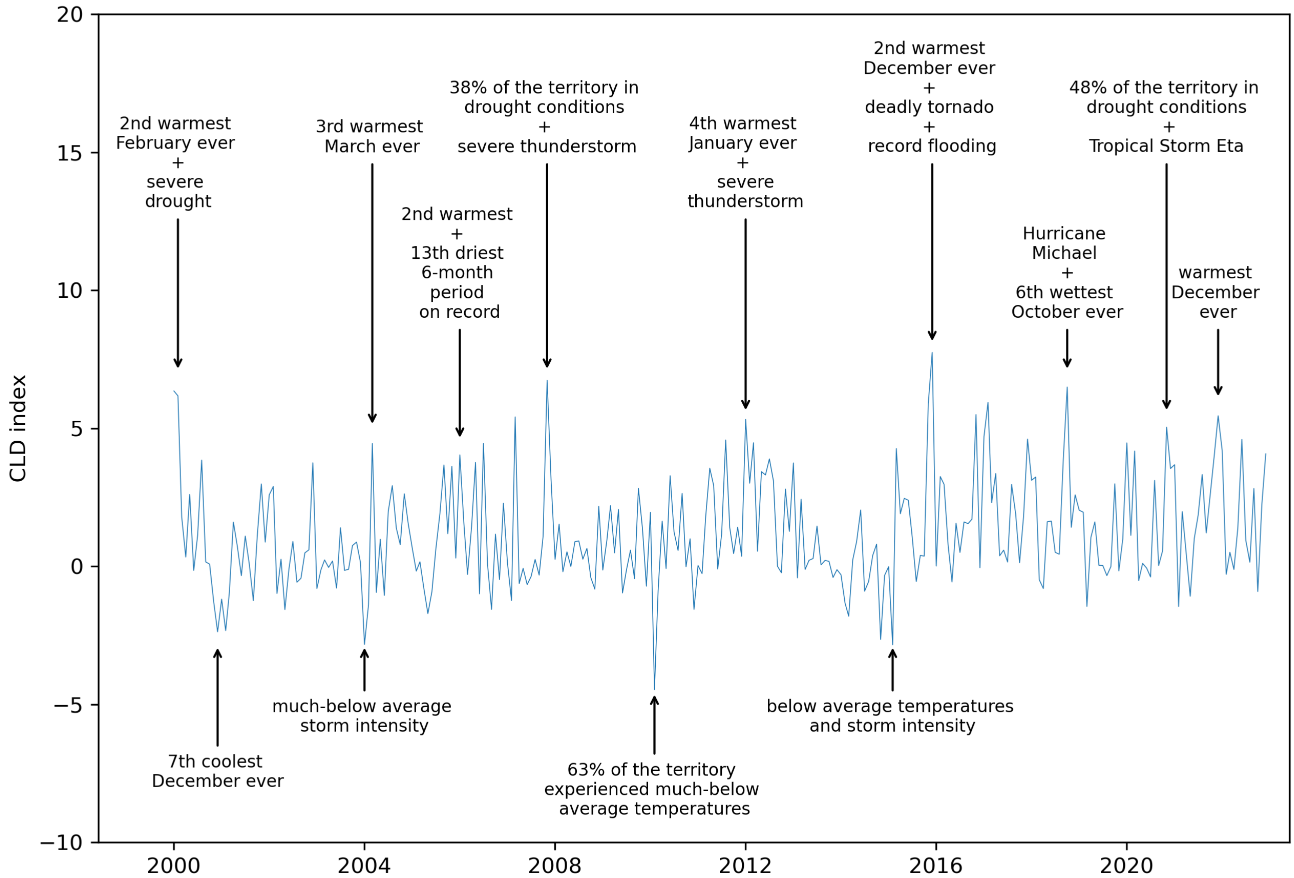
[8]For each climate division in the CONUS, monthly station temperature and precipitation values are computed from the daily observations. The divisional values are weighted by area to compute state-wide, regional, and national values.

[9]Having lack of access to detailed plant-level data on U.S. firms, I follow the existing literature (e.g., Pirinsky and Wang (2006); Korniotis and Kumar (2013); Huynh et al. (2020)) and determine a firm's location as the location of its headquarter. Pirinsky and Wang (2006) identify a potential issue with this approach, in that Compustat only reports the current state of a firm's headquarter, which introduces noise in the measurement if the company has relocated. However, the authors document that the number of firms that relocate over time is generally very small. Over a 15-year period for a sample of more than 5000 firms, they only find 118 cases of headquarter relocation. Later, I also address this concern by re-estimating the baseline regression using the firm's headquarter locations from the SEC 10-K/Q filings. Results are presented in Columns 1-2 of Table 9.

in vulnerable, but not directly affected areas, can still respond to salient disasters. As a specific example, Addoum, Eichholtz, Steiner, and Yönder (2021) document that coastal housing prices in Boston were negatively affected by Hurricane Sandy, even in the absence of direct damages (the hurricane only struck New York and New Jersey). The reasoning is because the hurricane increases the salience of climate-related risks to which coastal Boston properties are exposed to.

To illustrate that the indices capture salient climate events, Figure 1 shows a time series of the national climate disaster index for the Contiguous United States from Jan. 2000 to Dec. 2022. The climate risk index spikes during salient climate events, such as record flooding, severe droughts (e.g., 48% of the territory in drought conditions), heatwaves (e.g., the warmest December ever in 2021 since records began in 1895), or storms (e.g., Hurricane Michael). The state-level climate disaster indices are shown in the Appendix (Figure 4). The correlation heatmap (Figure 3) and the mean value by state (Table 7) are also reported in the Appendix.

Figure 1: Climate Disaster Index ($\mathbf{CLD_t}$).



This figure shows the climate disaster index from Jan. 2000 to Dec. 2022, annotated with climate-relevant events.

3.2.1 External validation of the climate disaster indices

After constructing the disaster indices, I conduct an analysis to validate that they not only capture potential material risks to firms, but also market-wide concern about physical climate risks which can propagate to U.S. firms via their respective climate disaster betas. I obtain external datasets to validate the climate disaster indices. The first dataset is the Media Climate Change Concerns index (MCCC) of Ardia, Bluteau, Boudt, and Inghelbrecht (2022) that has been used in the economics literature (for example, Pástor et al. (2022)). This index, which is available from January 2003 through June 2018, is constructed using data from major U.S. newspapers and newswires. It captures the number of climate news stories each day as well as their negativity and focus on risk. The MCCC index is at the country-level and divided into subindices related to different topics. I collect the subindices relevant to this study's climate disaster index, that is, extreme temperatures, hurricanes/floods, and water/drought. The second external dataset is used to validate the state-level index. It is the monthly Google Search Volume Index (SVI) of the topic "climate change" in the 48 states of the Contiguous U.S. from 2004 (when Google Trends began to provide data) to 2022. The idea follows Choi et al. (2020) who use SVI of the topic "global warming" to study investor attention to abnormal temperatures. To capture changes in attention, I calculate the log monthly change in the Google Search Volume Index, DSVI. $DSVI_{s,t}$ is the log change in SVI in state s in month t, adjusted for seasonality[10].

I then run regressions of each subindex of the MCCC (extreme temperatures, hurricanes/floods, and water/drought) on the national climate disaster index:

$$sub\_MCCC_t = \theta_0 + \theta_1 CLD_t + \kappa_t + \varepsilon_t, \tag{1}$$

where κ is month-of-the-year fixed effects to control for seasonality, and a regression of Google search volume for "climate change" on the state-level climate disaster index:

$$DSVI_{s,t} = \tau_0 + \tau_1 CLD_{s,t} + \eta_t + \varepsilon_t, \tag{2}$$

where $s = 1, 2, ..., 48$, and η_t is year-month fixed effects. The coefficients of interest are θ_1 and

[10]DSVI is defined as the residuals from the regression of the log change in the monthly SVI on month-of-the-year dummies. The residuals are then winsorized at the top and bottom 1% tails.

τ_1, respectively.

Table 1: MCCC, Google search volume for "climate change" and climate disasters

	(1) MCCC (extreme temperatures)	(2) MCCC (hurricanes/floods)	(3) MCCC (drought)	(4) DSVI
CLD_t	0.029**	0.035**	0.029**	
	(0.014)	(0.015)	(0.145)	
$CLD_{i,t}$				0.003**
				(0.001)
Month-of-the-Year FE	Yes	Yes	Yes	No
Year - Month FE	No	No	No	Yes
N.o. Obs.	186	186	186	10,425
R^2	0.064	0.075	0.057	0.388

This table reports the regression coefficients obtained from regressing the MCCC subindices and DSVI on the national and state-level climate disaster indices, respectively. In Columns 1-3, I regress the measures of media attention to extreme temperatures, hurricanes/floods and drought on the national climate disaster index (CLD_t), respectively. These regressions contain month-of-the-year fixed effects. Standard errors are robust to heteroskedasticity and shown in parentheses. In Column 4, $DSVI$ is the monthly log change of Google's search volume index (SVI) of the topic "climate change" (adjusted for seasonality) in each of the 48 states in the Contiguous U.S., and $CLD_{s,t}$ is the state-level climate disaster index. This regression contains year-month fixed effects. Standard errors are clustered at the state-level and shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 1 reports the results. In Columns 1-4, the coefficient estimates of the climate disaster risk measures are significantly positive, which demonstrate the validity of the indices constructed in this paper. This analysis shows that the presence of climate disasters at the country-level is associated with a significant increase in media coverage of news related to physical climate risk. Likewise, the occurrence of disasters at the state-level shows that people pay more attention to climate change when they are experiencing extreme weather events. In summary, Table 1 suggests that the indices capture meaningful events that correlate with increases in the salience of climate-related risks. Recent literature on climate change shows that personal experience with extreme weather events leads to an increased perception of climate risk (Akerlof, Maibach, Fitzgerald, Cedeno, and Neuman (2013); Zaval, Keenan, Johnson, and Weber (2014); Konisky, Hughes, and Kaylor (2016); Joireman, Truelove, and Duell (2010)). Therefore, if investors revise their beliefs about climate change, these may be reflected in prices and trading behavior. For instance, they will require higher future returns from riskier/vulnerable stocks (lower β^{CLD}) and accept lower future returns to hold safer/resilient stocks (higher

β^{CLD}) to disasters.

3.3 Stock and Company Information

I obtain monthly stock return data from the Center for Research in Security Prices (CRSP) and firm-level accounting data from Compustat. I consider all common stocks headquartered in one of the 48 states of the Contiguous U.S. in the CRSP trading database on the NYSE, AMEX, and NASDAQ from January 1, 2000 through December 31, 2022. All returns are converted into excess returns using the 1-month T-Bill rate obtained from Ken. French's Data Library[11].

3.4 Climate Disaster Beta

Following standard empirical literature[12], in each month of the time series, I estimate a climate disaster beta for all stocks i in the respective cross-section. This is done through the following time series regression with a rolling window, comprising the 60 months prior to the evaluation date:

$$r_{i,s,t} = \alpha + \beta^{CLD} CLD_{s,t} + \beta^{MKT} MKT_t + \varepsilon_{i,t}, \tag{3}$$

where $r_{i,s,t}$ is the excess return of stock i headquartered in state s in month t, $CLD_{s,t}$ is the state-level climate disaster index for state s in month t, and MKT_t is the market excess return. For month t, the rolling window covers month $t-59$ to month t. The 60-month rolling window ensures a sufficiently large number of observations for stable estimates and accounts for any potential time-varying character of physical climate risk[13]. This approach does not take an a priori view on which assets gain or lose when climate shocks occur, instead, it learns this from assets' return performance during past climate risk realizations. It is important to note that climate disasters are exogenous relative to a long list of reduced-form return-based factors that are popular in empirical asset pricing. Therefore, while I control for market (as motivated by the theory), I do not include any empirical factors in our baseline specification, similar to Bansal et al. (2019).

[11] I thank Ken. French for making this data available on his website: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data library.html.

[12] For example, Pástor and Stambaugh (2003) use this method for sensitivities to liquidity shocks, Ang, Hodrick, Xing, and Zhang (2006) for aggregate volatility shocks, Bansal et al. (2019) for long-run temperature fluctuations, and Huynh and Xia (2021) for climate change news risk.

[13] I require at least 24 months of return observations to construct the climate disaster beta.

Economically, stocks of firms that are more vulnerable to climate disasters will exhibit excess returns with lower β^{CLD}. On the other hand, stocks of firms that are more resilient to climate disasters will have excess returns with higher β^{CLD}. I therefore expect to find a premium on the former relative to the latter when assessing the effect of the climate disaster beta on future returns.

3.4.1 Sector variation

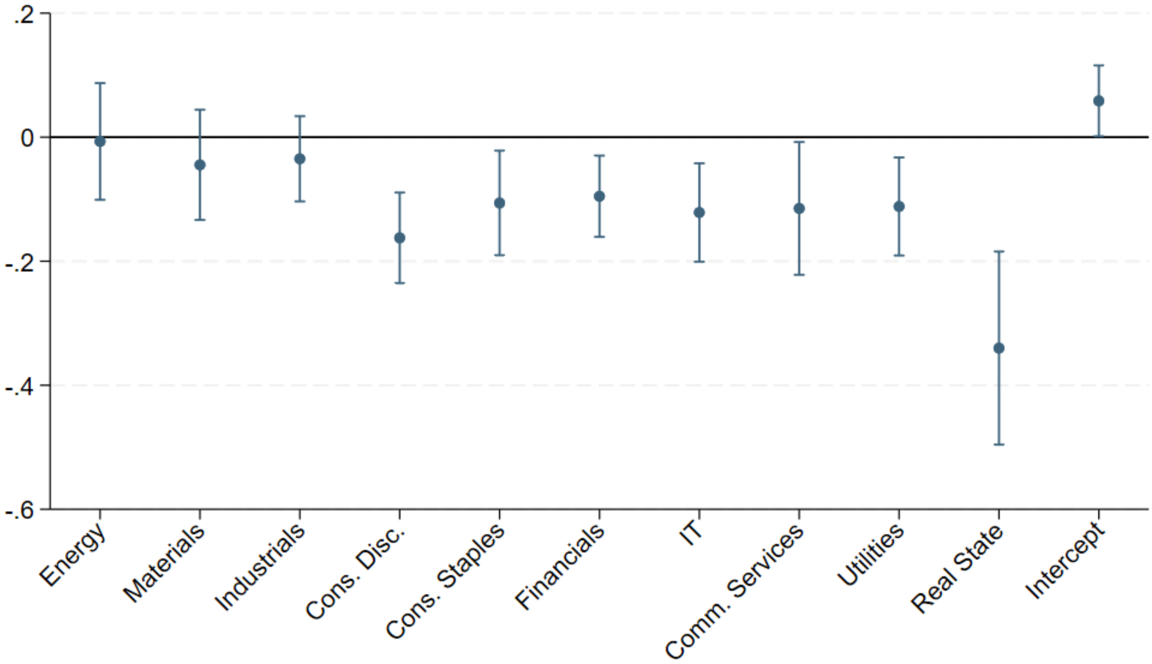
In particular, sectors might differ inherently in their exposure to physical climate risk, thus I examine sector variations in the climate disaster betas. I regress climate disaster betas on sector dummies (two-digit GICS), while controlling for time fixed effects. Figure 2 plots the coefficients from regressing β^{CLD} on the GICS 2-digit dummies. Specifically, I run:

$$\hat{\beta}_{i,t}^{CLD} = \eta + \sum_{s=1}^{10} \mathbb{I}[s_i = s] + \mu_t + \varepsilon_{i,t}, \tag{4}$$

where $\hat{\beta}_{i,t}^{CLD}$ is firm i's climate disaster beta at the end of month t, j denotes GICS industry sectors, $\mathbb{I}[j_i = j]$ indicates whether or not stock i's industry classification belongs to sector j, and μ_t is time fixed effects. The reference sector (intercept η) is Health Care (GICS 35). The coefficients of the other sectors are interpreted as the difference between the expected climate disaster beta in that sector and the Health Care sector.

Figure 2 shows that Health Care is one of the least vulnerable sector to climate disasters. The Health Care sector has a small demand elasticity, and therefore may provide a good hedge against negative shocks. This is also consistent with Malik and Faff (2022) who find that industries related to health services earn high returns after disasters with human casualty. Previous literature shows that physical climate risk systematically affects a large cross section of industries (e.g., Balvers, Du, and Zhao (2017); Colacito, Hoffmann, and Phan (2019); Huynh et al. (2020); Braun, Braun, and Weigert (2021)). For instance, sectors with a significant portion of their business activities taking place outdoors tend to be more subject to disruptions caused by natural disasters, such as Communication Services and Real State. Moreover, a negative coefficient for Financials is plausible since the insurance industry is expected to be negatively exposed to realizations of physical climate risk, due to higher insurance claims following disasters. Disasters may also affect household demand in the retail sector. Graff Zivin and Neidell

Figure 2: Sector Variations in β^{CLD}.



(2014) find that temperature increases reduce time allocated to outdoor leisure, which might induce consumers to spend less time shopping. Finally, I cannot reject the coefficients from Energy, Materials, and Industrials to be different from zero, that is, these sectors are viewed as being as resilient as Health Care. This might be related to a local demand surge for these sectors when rebuilding begins post disaster.

3.4.2 Correlations with Firm Characteristics

In this section, I investigate how firm characteristics correlate with physical climate risk exposure. Firm characteristics are known to be related to climate risk exposure, see, for example, Hsu et al. (2018), Sautner et al. (2023), and Li et al. (2024). I estimate the regression of one-month ahead β^{CLD} on the control accounting variables in our baseline regression (5), that is, Size, Market/Book, ROE, Debt/Assets, CapEx/Assets, PP&E/Assets, and R&D/Assets. I cluster standard errors by firms, as residuals within firms are correlated over time. I optionally include industry and firm's headquarter state fixed effects to control for variation that can be attributed to sector or regional differences. The model includes time-fixed effects to exploit the cross-sectional variation in climate disaster beta estimates and to help mitigate omitted variable bias by controlling for unobserved effects that vary over time but not over firms.

Table 2: Firm-level Correlates of Climate Disaster Beta

	Dependent Variable: Future β^{CLD}		
	(1)	(2)	(3)
Size	0.007	0.005	0.004
	(0.007)	(0.007)	(0.007)
Market/Book	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)
ROE	-0.051*	-0.055*	-0.056*
	(0.029)	(0.030)	(0.030)
Debt/Assets	-0.128***	-0.117**	-0.120**
	(0.049)	(0.050)	(0.050)
CapEx/Assets	0.480*	0.453*	0.545**
	(0.263)	(0.263)	(0.257)
PP&E/Assets	-0.054	-0.129**	-0.130**
	(0.041)	(0.057)	(0.057)
R&D/Assets	0.682	0.911	0.768
	(0.646)	(0.680)	(0.678)
Year-Month FE	Yes	Yes	Yes
Sector FE	No	Yes	Yes
State FE	No	No	Yes
N.o. Obs.	278,288	278,288	278,288

This table reports the regression coefficients obtained from regressing β^{CLD} on lagged values of natural logarithm of market capitalisation, market-to-book ratio, return on equity, book leverage, investment-to-assets, PP&E-to-assets, R&D-to-assets, respectively. The sample period is from January 2000 to December 2022. Regressions may contain year-month, industry and state fixed effects. Standard errors are clustered at the firm level and shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2 reports the estimates. I focus on the regression specification that includes sector and state fixed effects, which leads to identification coming from the cross-section of firms active in the same sector and in the same state, respectively. Similar to what Hsu et al. (2018) find, negative correlates of physical climate risk exposure are leverage (Debt/Assets) and physical capital intensity (PP&E/Assets). In detail, capital-constrained firms are less able to adapt and recover from disasters, while firms holding more physical assets are more vulnerable to damages caused by climate disasters. In turn, positive correlates are those related to capital expenditures (CapEx/Assets) and firm valuation (Market/Book). Previous literature, such as Hsu et al. (2018) and Sautner et al. (2023), has shown that firms who actively invest can respond more adaptively to extreme situations because they possess greater resourcefulness and flexibility, and face lower costs to develop recovery solutions to natural disasters.

3.5 Sample and Summary Statistics

The sample employed in this study is the intersection of stock data from the Center for Research in Security Prices (CRSP), and accounting data from the Compustat Quarterly and Annual Fundamentals files[14]. Following Lioui and Tarelli (2022), micro-cap stocks (market equity $<$ NYSE 30th percentile), as well as observations where the stock price is below US$1 are dropped at each time t. These choices follow a large literature on the effect of micro-cap stocks on asset-pricing anomalies and the difficulty in trading them (Fama and French (2008); Hou, Xue, and Zhang (2020); Jensen, Kelly, and Pedersen (2023))[15]. To mitigate the impact of outliers, I winsorize all continuous variables at their 1st and 99th percentiles. After applying the aforementioned restrictions on the data and requiring stocks to have sufficient data to estimate betas, the main sample contains 246,941 stock-month observations from Jan. 2000 to Dec. 2022 covering 2,501 unique firms. Table 3 reports summary statistics for the key variables used in the baseline analysis.

Over the sample period, the average monthly stock excess return is 1.10%. The representative firm has a climate disaster beta (national) of -0.08 and a climate disaster beta (state) of -0.03. Moreover, the average firm size (measured by the natural logarithm of market capitalization) is about $3.8 billion. Average market-to-book ratio (Market/Book), book leverage (Debt/Assets), capital expenditures-to-total assets ratio (CapEx/Assets), research and development expenses-to-total assets ratio (R&D/Assets), property, plant and equipments-to-total assets ratio (PP&E/Assets) equal 3.75, 0.25, 0.03, 0.01, 0.24, respectively. The average firm has an annual return on equity (ROE) of 0.02, a market beta (CAPM Beta) of 1.13 and idiosyncratic volatility of 7.96.

[14]Following Koijen and Yogo (2019), I merge the CRSP data with the most recent Compustat data as of at least 6 months and no more than 18 months prior to the trading date. The lag of at least 6 months ensures that the accounting data were public on the trading date.

[15]Harvesting the climate disaster beta from microcaps would be difficult for a real-time investor, as these stocks are illiquid.

Table 3: Summary statistics

				Percentiles		
	N.o. Obs.	Mean	SD	25%	Median	75%
Excess Return (%)	396,876	1.099	12.598	-5.026	0.913	6.781
Size	396,775	22.073	1.270	21.137	21.835	22.849
Market/Book	389,596	3.748	6.515	1.542	2.450	4.290
ROE	389,712	0.024	0.166	0.011	0.030	0.052
Debt/Assets	369,995	0.254	0.202	0.086	0.235	0.372
CapEx/Assets	380,055	0.028	0.038	0.005	0.015	0.035
PP&E/Assets	383,125	0.243	0.239	0.055	0.155	0.365
R&D/Assets	398,114	0.008	0.019	0	0	0.007
Climate Disaster Beta (national)	302,516	-0.078	0.809	-0.466	-0.060	0.299
Climate Disaster Beta (state)	302,516	-0.026	0.762	-0.403	-0.027	0.356
Idiosyncratic Volatility	298,980	7.956	4.110	5.055	7.007	9.816
CAPM Beta	334,932	1.126	0.663	0.666	1.050	1.474
Momentum	347,679	0.092	0.396	-0.138	0.062	0.269
Climate Disaster Index (national)	276	1.044	1.991	-0.263	0.617	2.082
Climate Disaster Index (state)	13,248	1.153	2.010	-0.105	0.787	2.382

4 Empirical Results

4.1 Climate Disaster Beta and Future Returns

In this section, I examine the relation between a stock's climate disaster beta and future returns at the firm-month level. Similar to prior literature on stock returns and climate risks (Huynh and Xia (2021); Bolton and Kacperczyk (2021); Huij et al. (2022)), I include various firm-level variables in the baseline specification, as follows:

$$r_{i,t+1} = \alpha + \gamma\hat{\beta}^{CLD}_{i,t} + \lambda X_{i,t} + c_j + \mu_t + \delta_s + \varepsilon_{i,t} \tag{5}$$

where $r_{i,t+1}$ is the excess return on firm i's stock in month $t+1$, $\hat{\beta}^{CLD}_{i,t}$ is firm i's climate disaster beta in month t estimated in equation (3), $X_{i,t}$ is a vector of firm characteristics (i.e., Size, Market/Book, ROE, Debt/Assets, CapEx/Assets, PP&E/Assets, R&D/Assets, CAPM Beta, Idiosyncratic Volatility, and Momentum), and c_j, μ_t, and δ_s are the sector (two-digit GICS), time, and firm's headquarter state fixed effects, respectively. For ease of interpretation of the coefficient estimates, I multiply the returns by 100.

Following contemporary asset pricing research (e.g., Ben-Rephael, Carlin, Da, and Israelsen (2021); Huynh and Xia (2021)), I estimate equation (5) using panel regression analysis and controlling for industry, year-month, and headquarters' state fixed effects. The inclusion of these fixed effects accounts for unobserved heterogeneity across sectors, macroeconomic trends, inter-year seasonality effects, and time-invariant state factors. Moreover, Petersen (2008) shows that panel regressions with fixed effects allow researchers to improve the efficiency of estimates and straightforwardly compute standard errors clustered at the firm level, making the estimated coefficients and standard errors more robust than those obtained from the traditional Fama–MacBeth framework.

Table 4 reports the results from the regression of one-month-ahead stock excess returns on climate disaster betas. Column 1 reports the result of the regression without control variables. Column 2 presents the results of the baseline regression with firm-level control variables. Across the two model specifications, the point estimates on β^{CLD} are negative and statistically significant, indicating a negative relation between the climate disaster beta and future stock returns.

The coefficients are also economically significant. For example, in Column 2 of Table 4, the coefficient estimate on β^{CLD} of -0.065 indicates that a one-standard-deviation increase in the climate disaster beta is associated with a drop of 4.95 bps ($= -0.065 \times 0.762$) in the next month's stock excess return, which is equivalent to a decrease of 4.51% relative to the sample mean of excess returns. These results are consistent with Hypothesis 1, as well as the prediction of the rare-disaster literature on the asset pricing implications of climate disaster risk. Since stocks with a higher β^{CLD} perform better as the climate disaster index increases, investors view these stocks as more resilient (safer) to physical climate risk. Therefore, investors are willing to pay higher prices for stocks with a higher β^{CLD} and to accept lower future returns on these stocks.

To elaborate on the economic significance of our results, compare the effect of β^{CLD} to that of CAPM Beta, which is known to be a strong predictor of future stock returns. The estimated coefficient on CAPM Beta in Columns 2 is around 0.16, meaning that a one-standard-deviation increase in CAPM Beta is associated with an increase of 10.61 bps ($= 0.16 \times 0.663$) in the next month's excess return, which is equivalent to an increase of 9.65% relative to the sample mean. The effect of β^{CLD} on future excess returns therefore appears to be smaller than the effect of CAPM Beta. The relatively smaller effect of β^{CLD} is expected given that exposure to market (systemic) risk is more incorporated into asset prices than climate risk. Finally, the coefficients on the other control variables are also consistent with prior literature. Specifically, Column 2 of Table 4 shows that future returns are negatively associated with firm size and momentum but positively associated with leverage (Debt/Assets) and CAPM (market) beta.

Table 4: Climate Disaster Beta and Future Returns

	Dependent variable: Future excess returns		
	(1)	(2)	(3)
β^{CLD}	-0.042*	-0.065**	0.003
	(0.024)	(0.028)	(0.042)
$\beta^{CLD} \times High\_CLD_{s,t}$			-0.137**
			(0.062)
Size		-0.157***	-0.157***
		(0.015)	(0.015)
Market/Book		-0.005	-0.005
		(0.004)	(0.004)
ROE		0.189	0.189
		(0.159)	(0.159)
Debt/Assets		0.210**	0.210**
		(0.105)	(0.105)
CapEx/Assets		-0.548	-0.556
		(0.816)	(0.817)
PP&E/Assets		0.122	0.123
		(0.136)	(0.136)
R&D/Assets		3.076*	3.091*
		(1.843)	(1.841)
CAPM Beta		0.162***	0.162***
		(0.036)	(0.036)
Idio. Volatility		0.002	0.002
		(0.007)	(0.007)
Momentum		-0.360***	-0.359***
		(0.065)	(0.065)
Year - Month FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
N.o. Obs.	296,891	246,941	246,941
Adj. R^2	0.274	0.280	0.280

This table reports the regression coefficients obtained from regressing future monthly stock excess returns on estimates of climate disaster beta in the previous month. The sample period is from January 2000 to December 2022. The regression optionally includes the natural logarithm of market capitalisation, Market/Book, ROE, Debt/Assets, CapEx/Assets, PP&E/Assets, R&D/Assets, CAPM beta, Idiosyncratic Volatility, and Momentum as control variables. Regressions contain year-month, industry and state fixed effects. Standard errors are clustered at the firm level and shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

4.2 Time-Varying Climate Disaster Premium

I next examine Hypothesis 2, which posits that the effect of the climate disaster beta on future stock returns changes over time and is more pronounced following times of heightened physical climate risk. I define a month as having a high physical risk if the monthly state-level climate disaster index is greater than its median value; otherwise, the month has a low climate disaster index. Accordingly, I construct the dummy variable $High\_CLD_{s,t}$, which is equal to 1 for months with high physical climate risk, and 0 otherwise. I interact $High\_CLD_{s,t}$ with $\hat{\beta}_{i,t}^{CLD}$ and reexamine the baseline regression (5) by including this interaction term. Table 4 reports the estimation results.

Consistent with the prediction of Hypothesis 2, Table 4 shows that the coefficient on the interaction term between $High\_CLD_{s,t}$ and β^{CLD} is negative and significant, indicating that, during times when the climate disaster index is high, the impact of the climate disaster beta on future stock returns is significantly greater compared to low climate disaster index periods. In particular, the coefficient estimate in Column 3 suggests that, during times of a high physical climate risk (i.e., $High\_CLD_{s,t} = 1$), a one-standard-deviation increase in β^{CLD} is associated with a total reduction of 10.21 bps in future excess returns, which is equivalent to a drop of 9.29% relative to the sample mean[16].

This finding is also consistent with investors' intertemporal hedging demand becoming more pronounced following times of heightened disaster risk (Bloom (2009); Bekaert, Hoerova, and Duca (2013); Bali, Brown, and Tang (2017); Huynh and Xia (2021)). Specifically, major, highly salient climate events are expected to increase investors' risk aversion, and thus, they would be willing to accept even lower future returns from stocks with a higher climate disaster beta for hedging purposes in times of high physical climate risk.

4.3 Geographic Dispersion, Cash Holdings and the Climate Disaster Premium

The previous sections show that investors prefer high-β^{CLD} stocks because of their resilience to climate disaster risk. In this section, I empirically test Hypothesis 3 by exploring whether

[16] This is computed as $(0.003 - 0.137) \times 0.762 = 10.21$ bps, where 0.003 and 0.137 are the coefficients on β^{CLD}, and $\beta^{CLD} \times High\_CLD_{s,t}$, respectively, and 0.762 is the standard deviation of β^{CLD}.

organizational structure and corporate policies matter for determining a firm's vulnerability to climate disasters. I posit that, when physical climate risk is high, investors will value stocks of firms that either diversify their operations geographically or hold large amounts of cash, which provide more effective hedges against future realizations of climate disasters.

I define *Cash Holdings* as cash and cash equivalents scaled by total assets. I further employ two alternative proxies for a firm's geographical dispersion. First, I obtain data on the number of corporate geographical segments from the Compustat Historical Segments data file. I split the sample by the number of geographical segments in a firm (*High_Geo_Seg* vs. *Low_Geo_Seg*, i.e., above yearly median vs. below yearly median). Second, I obtain subsidiary data from Wharton Research Data Services (WRDS) which contains parent company and subsidiary relationships for companies filing[17]. Again, I split the sample by the number of subsidiaries in a firm (*High_Subsid* vs. *Low_Subsid*, i.e., above yearly median vs. below yearly median). I lag the variables before matching the data with our baseline sample to allow ample time for the market to incorporate the information into stock prices.

I estimate the regression of climate disaster beta on lagged values of *High_Geo_Seg*, *High_Subsid*, *Cash Holdings*, interaction terms between these variables and *High_CLD*, and the same set of control variables in our baseline regressions. Table 5 reports the estimation results. The estimated coefficients on the interaction terms are positive and significant at the 1% level. These results are consistent with stocks of geographically dispersed firms arguably having better potential to hedge against climate disaster risk than those of local firms given they have stronger economic interests outside their headquarters state. The results also show that the hedging effect from cash holdings proves beneficial for firms when a cash flow shortfall materializes (e.g., during climate disaster periods). In summary, Columns 1-3 indicate that firms with high geographical dispersion and larger cash holdings are perceived as less vulnerable to local climate disaster risk.

[17]Data is parsed from exhibits attached to a variety of filing types (10-K, 10-Q, etc.), but relies primarily on Exhibit 21.

Table 5: Geographic Dispersion, Cash Holdings and Climate Disaster Beta

	Dependent variable: Future β^{CLD}		
	(1)	(2)	(3)
High_Geo_Seg	-0.003		
	(0.022)		
High_Geo_Seg × High_CLD	0.017***		
	(0.006)		
High_Subsid		-0.036*	
		(0.019)	
High_Subsid × High_CLD		0.018***	
		(0.005)	
Cash Holdings			0.045
			(0.046)
Cash Holdings × High_CLD			0.061***
			(0.015)
Control Variables	Yes	Yes	Yes
Year - Month FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
N.o. Obs.	240,108	224,776	193,212

This table reports the effect of geographic dispersion and cash holdings on climate disaster betas. Columns 1-3 report the results of the analysis based on the national climate disaster index. Columns 4-6 report the results of the analysis based on the state-level climate disaster indices. The sample period is from January 2000 to December 2022. The regression includes the natural logarithm of market capitalisation, market-to-book ratio, return on equity, book leverage, investment-to-assets, PP&E-to-assets, R&D-to-assets, CAPM beta, idiosyncratic volatility, and 12-month momentum as control variables. Regressions contain year-month, industry and state fixed effects. Standard errors are clustered at the firm level and shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

5 Robustness Tests

In this section, I conduct a battery of tests to check the robustness of the findings. First, since Table 4 shows a significant negative effect of the climate disaster beta on future excess returns, a natural question arises as to whether β^{CLD} has long-term predictive power for future excess returns. I test this question by regressing future excess returns from month $t+2$ to month $t+12$ on β^{CLD} measured in month t. Overall, the results reported in Table 8 in the Appendix indicate that the predictive power of β^{CLD} remains mostly significant when predicting future 2- to 12-month returns. The fact that the effect remains significant beyond month $t+1$ suggests that the results are not driven by a short-run reversal effect (Jegadeesh (1990)).

Second, I address the concern that Compustat database contains only the current headquarter state information by re-estimating the baseline regression using the firm's headquarter locations from the SEC 10-K/Q filings. Results are presented in Columns 1-2 of Table 9. To obtain the firms' historical headquarter states, I employ the dataset from Gao, Leung, and Qiu (2021)[18]. They start with the dataset from Bai, Fairhurst, and Serfling (2020) for the period before 2003[19], whereas for the period after 2003, the authors extract for each firm-year the headquarter state from the latest SEC 10 K/Q filing using the Augmented 10-X Header Data provided by the Notre Dame Software Repository for Accounting and Finance.

Third, given climate disasters are exogenous relative to a long list of reduced-form return-based factors that are popular in empirical asset pricing, I choose only to control for the market factor (as motivated by the theory) in the baseline specifications. However, I show that our results are robust to including empirical factors, such as the five-factor model of Fama and French (2015). Results are presented in Columns 3-4 of Table 9. In summary, Table 9 shows the negative relation between climate disaster beta and future returns, especially during times of heightened disaster risk, consistent with Hypothesis 2.

Finally, it would be useful to examine whether the baseline findings hold for disasters at the national level. As mentioned before, the national index can better capture general equilibrium and spillover effects, that is, asset prices in vulnerable, but not directly affected areas, can still respond to salient disasters that signal worsening climate conditions. Thus, I run regression (3) replacing the state-level index, $CLD_{s,t}$, for the national index, CLD_t, to obtain the climate disaster beta for disasters at the national level. Next, I assess the effect of $\beta^{CLD}_{national}$ on future excess returns. Table 6 reports the results. The estimated coefficients have similar magnitude to the ones when considering state-level disasters. For example, in Column 2, the coefficient estimate on $\beta^{CLD}_{national}$ of -0.071 indicates that a one-standard-deviation increase in the climate disaster beta is associated with a drop of 5.74 bps ($= -0.071 \times 0.809$) in the next month's stock excess return, which is equivalent to a decrease of 5.23% relative to the sample mean of excess returns. Moreover, consistent with the prediction of Hypothesis 2, Column 3 shows that the coefficient on the interaction term between $High\_CLD_t$ and $\beta^{CLD}_{national}$ is negative and significant at the 1% level, indicating that following times when the climate disaster index is high, the

[18] I thank the authors for making the data available at https://mingze-gao.com/posts/firm-historical-headquarter-state-from-10k/

[19] The dataset of firm historical headquarter state is based on the SEC filings post 1994 and hand-collected by the authors from the Moody's Manuals (later Mergent Manuals) and Dun & Bradstreet's Million Dollar Directory (later bought by Mergent).

impact of the climate disaster beta on future stock returns is significantly greater compared to low climate disaster index periods. In detail, the coefficient estimates in Column 3 suggests that, during times of high physical climate risk (i.e., $High\_CLD_t = 1$), a one-standard-deviation increase in $\beta^{CLD}_{national}$ is associated with a total reduction of 13.27 bps in future excess returns, which is equivalent to a drop of 12.07% relative to the sample mean[20]. These results suggest that climate disasters at the national level are also priced in the cross-section of stock returns, consistent with our central hypotheses.

6 Conclusion

This study investigates whether climate disaster risk is priced in the cross-section of U.S. stock returns. I construct national and state-level climate disaster indices and use them to estimate a climate disaster beta, β^{CLD}, that captures a stock return's covariance with the physical climate risk indices. Empirical results show that stocks with a higher β^{CLD} are associated with lower future returns and the effect of β^{CLD} is more pronounced during periods of high climate disaster risk. Further analysis suggests that, when market-wide concern about climate change risk is elevated, the stocks of firms with geographically dispersed business operations or high cash holdings have a higher β^{CLD}. These results are consistent with the hypothesis of the rare-disaster literature, which posits that the value loss suffered by assets in a disaster varies both in the cross-section and over time. Particularly, when a stock is expected to do well in a disaster, investors are optimistic about its resilience, thus such asset has a higher price, and a lower future return.

Investors can use our indices to create climate-resilient investment strategies. Climate disaster beta could thus be used by practitioners for whom it is too costly to make use of commercial or text-based alternatives (for example, earnings call transcripts). The methodology adopted here might also be valuable to academics in assessing the asset pricing implications of climate risk, as the approach is easily replicated. Moreover, regulators and policymakers could use the climate disaster indices to quantify physical climate risk and the climate disaster betas to identify highly exposed firms, sectors, and states.

[20] This is computed as $(0.011 - 0.175) \times 0.809 = 13.27$ bps, where 0.011 and -0.175 are the coefficients on $\beta^{CLD}_{national}$ and $\beta^{CLD}_{national} \times HIGH\_CLD_{national}$, respectively, and 0.809 is the standard deviation of $\beta^{CLD}_{national}$.

Table 6: Climate Disaster Beta (national) and Future Returns

	Dependent variable: Future excess returns		
	(1)	(2)	(3)
$\beta^{CLD}_{\text{national}}$	-0.066***	-0.071***	0.011
	(0.021)	(0.027)	(0.039)
$\beta^{CLD}_{\text{national}} \times High\_CLD_t$			-0.175***
			(0.060)
Size		-0.155***	-0.155***
		(0.015)	(0.015)
Market/Book		-0.005	-0.005
		(0.004)	(0.004)
ROE		0.194	0.192
		(0.159)	(0.159)
Debt/Assets		0.214**	0.214**
		(0.105)	(0.105)
CapEx/Assets		-0.538	-0.529
		(0.817)	(0.817)
PP&E/Assets		0.112	0.112
		(0.137)	(0.137)
R&D/Assets		3.257*	3.246*
		(1.846)	(1.845)
CAPM Beta		0.169***	0.170***
		(0.036)	(0.036)
Idio. Volatility		0.002	0.002
		(0.007)	(0.007)
Momentum		-0.362***	-0.363***
		(0.066)	(0.066)
Year - Month FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
N.o. Obs.	296,891	246,941	246,941
Adj. R^2	0.274	0.280	0.280

This table reports the regression coefficients obtained from regressing future monthly stock excess returns on estimates of climate disaster beta (national or state) in the previous month. The sample period is from January 2000 to December 2022. The regression optionally includes the natural logarithm of market capitalisation, Market/Book, ROE, Debt/Assets, CapEx/Assets, PP&E/Assets, R&D/Assets, CAPM beta, Idiosyncratic Volatility, and Momentum as control variables. Regressions contain year-month, industry and state fixed effects. Standard errors are clustered at the firm level and shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Climate disasters, gauged by intensity measures, provide variation that is plausibly exogenous to economic or societal outcomes and may serve as instrumental variable for many empirical questions. In that sense, there are several interesting and important topics to be investigated by future climate finance research. First, it is to understand better the mechanism through which climate disasters affect prices, for example, changes in cash flow risk related to direct damages and divestment in disaster-prone areas, or psychological factors affecting local investors' trading behavior. Second, it is to examine other effective ways firms can minimize the impact of climate disasters. Finally, the indices constructed here can be used, for instance, for testing the effect of climate disasters on different economic aggregates, such as in Felbermayr and Gröschl (2014), Colacito et al. (2019), and Tran and Wilson (2023).

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Appendix

Excess Return: monthly raw excess return of a stock over the risk-free rate. As risk-free rate, the 1-month T-bill rate is used. *Source*: CRSP, Ken. French's Data Library.

Size: the natural logarithm of a firm's equity market capitalization, defined as monthly share price multiplied by shares outstanding. *Source*: CRSP.

Market/Book: the equity market value (Size) at the end of the year divided by the difference between common equity (Compustat data item CEQ) and preferred stock capital (Compustat data item PSTK) at the end of the year. *Source*: Compustat, CRSP.

ROE: income before extraordinary items (Compustat data item IB) divided by common equity (Compustat data item CEQ). *Source*: Compustat.

Debt/Assets: long term debt (Compustat data item DLTTQ) plus debt in current liabilities (Compustat data item DLCQ), divided by total assets (Compustat data item ATQ). *Source*: Compustat.

CapEx/Assets: capital expenditures (Compustat data item CAPXQY) divided by total assets (Compustat data item ATQ). *Source*: Compustat.

PP&E/Assets: net property, plant and equipment (Compustat data item PPENTQ) divided by total assets (Compustat data item ATQ). *Source*: Compustat.

R&D/Assets: Research and development expenses (Compustat data item XRDQ) divided by total assets (Compustat data item ATQ). If missing, it is set equal to 0. *Source*: Compustat.

CAPM Beta: factor loading on the market factor from a CAPM 1-factor regression estimated based on a rolling window of 60 months. *Source*: CRSP, Ken. French's Data Library, estimated.

Idiosyncratic Volatility: the standard deviation of the residuals from a CAPM 1-factor regression estimated based on a rolling window of 60 months. *Source*: CRSP, Ken. French's Data Library, estimated.

Momentum: cumulative stock monthly returns over an 11-month period prior to month t. *Source*: CRSP, estimated.

Table 7: Climate Disaster Beta (mean by headquarter state) and $CLD_{s,t}$ (mean)

	$\beta^{CLD}_{national}$	β^{CLD}_{state}	CLD_{state}
AL	-0.066	-0.012	1.327
AZ	-0.111	-0.070	1.229
AR	-0.291	-0.269	1.022
CA	0.049	0.016	1.248
CO	-0.125	-0.105	1.144
CT	-0.112	0.027	1.066
DE	-0.154	-0.004	1.205
FL	-0.060	-0.098	1.260
GA	-0.129	0.074	1.429
ID	-0.336	-0.101	1.084
IL	-0.113	-0.121	1.136
IN	-0.168	-0.057	1.107
IA	-0.221	-0.045	0.934
KS	-0.216	-0.149	0.961
KY	-0.156	0.038	1.272
LA	-0.028	0.071	1.280
ME	0.273	0.308	1.055
MD	0.031	-0.101	1.197
MA	0.101	-0.075	1.063
MI	-0.276	0.024	1.003
MN	-0.111	-0.064	1.038
MS	-0.125	-0.025	1.278
MO	-0.153	-0.019	1.023
MT	-0.215	-0.160	0.989
NE	-0.123	-0.024	0.887
NV	0.024	-0.043	1.242
NH	0.141	0.272	1.182
NJ	-0.049	-0.080	1.030
NM	-0.164	-0.192	1.340
NY	-0.069	-0.045	1.118
NC	-0.045	0.076	1.250
ND	0.030	-0.164	0.928
OH	-0.182	0.044	1.058
OK	-0.235	-0.110	1.046
OR	-0.115	-0.003	1.017
PA	-0.104	-0.015	0.998
RI	-0.087	-0.089	1.014
SC	-0.203	-0.063	1.306
SD	-0.071	-0.240	0.951
TN	-0.179	0.066	1.259
TX	-0.095	0.004	1.199
UT	0.055	-0.143	1.210
VT	-0.062	0.178	1.228
VA	-0.115	-0.056	1.272
WA	-0.099	-0.066	1.053
WV	-0.354	-0.137	1.183
WI	-0.109	0.001	0.960
WY	-1.328	0.638	1.469

Table 8: Climate Disaster Beta and Return Predictability

	Dependent variable: Future excess returns										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$	$t+7$	$t+8$	$t+9$	$t+10$	$t+11$	$t+12$
$\beta^{CLD}_{\text{state}}$	-0.060**	-0.042	-0.045*	-0.079***	-0.077***	-0.083***	-0.079***	-0.082***	-0.091***	-0.076***	-0.055**
	(0.028)	(0.027)	(0.027)	(0.027)	(0.027)	(0.028)	(0.028)	(0.028)	(0.028)	(0.026)	(0.025)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year - Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N.o. Obs.	244,118	241,629	239,224	236,915	234,647	232,436	230,159	227,921	225,741	223,685	221,655
Adj. R^2	0.282	0.284	0.284	0.285	0.286	0.286	0.283	0.284	0.283	0.285	0.285

This table reports the regression coefficients obtained from regressing future monthly stock excess returns in month $t+2$ to $t+12$ on estimates of climate disaster beta (state) in month t. The sample period is from January 2000 to December 2022. The regression optionally includes the natural logarithm of market capitalisation, Market/Book, ROE, Debt/Assets, CapEx/Assets, PP&E/Assets, R&D/Assets, CAPM beta, Idiosyncratic Volatility, and Momentum as control variables in month t. Regressions contain year-month, industry and state fixed effects. Standard errors are clustered at the firm level and shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 9: Climate Disaster Beta, SEC headquarter, and Fama-French 5-factor model

	Dependent variable: Future excess returns			
	(1)	(2)	(3)	(4)
	SEC headquarter	SEC headquarter	FF5	FF5
β^{CLD}	-0.054*	0.016	-0.047*	0.067
	(0.028)	(0.042)	(0.028)	(0.043)
$\beta^{CLD} \times High\_CLD_{s,t}$		-0.141**		-0.227***
		(0.061)		(0.064)
Control Variables	Yes	Yes	Yes	Yes
Year - Month FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
N.o. Obs.	246,386	246,386	246,941	246,941
Adj. R^2	0.280	0.280	0.280	0.280

This table reports the regression coefficients obtained from regressing future monthly stock excess returns in month $t+2$ to $t+12$ on estimates of climate disaster beta (state) in month t. The sample period is from January 2000 to December 2022. The regression optionally includes the natural logarithm of market capitalisation, Market/Book, ROE, Debt/Assets, CapEx/Assets, PP&E/Assets, R&D/Assets, CAPM beta, Idiosyncratic Volatility, and Momentum as control variables in month t. Regressions contain year-month, industry and state fixed effects. Standard errors are clustered at the firm level and shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Figure 3: Correlation heatmap of the state-level climate disaster indices.

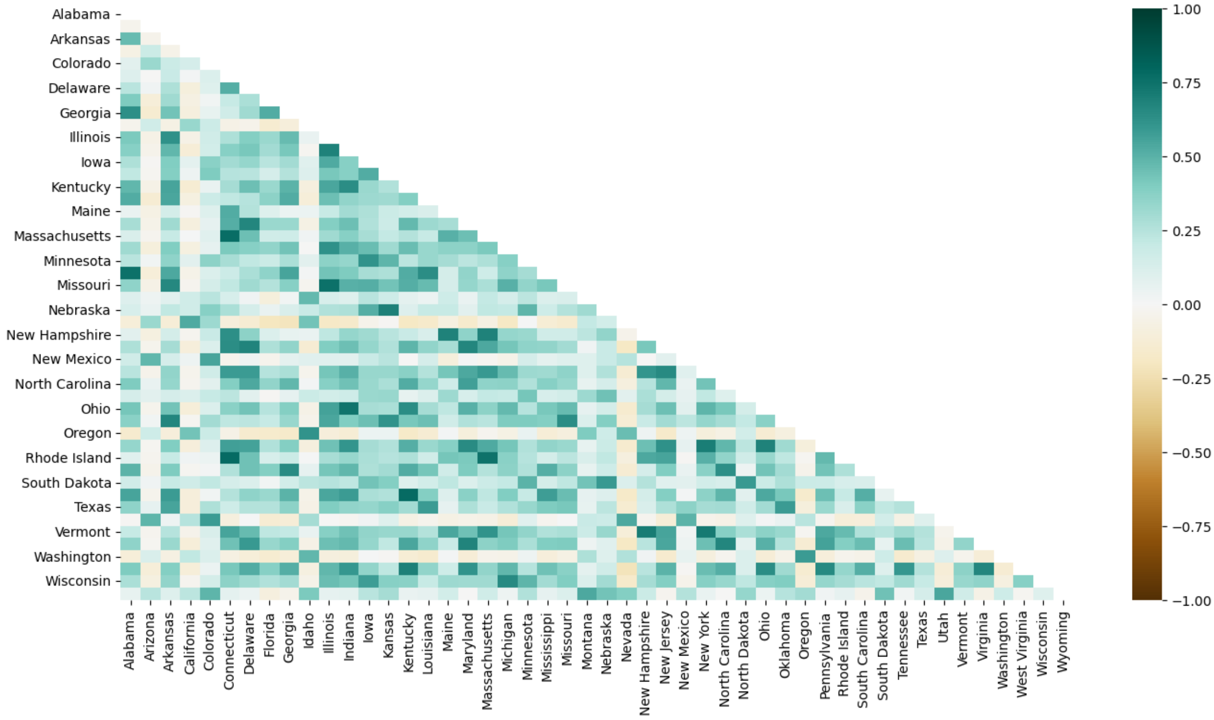
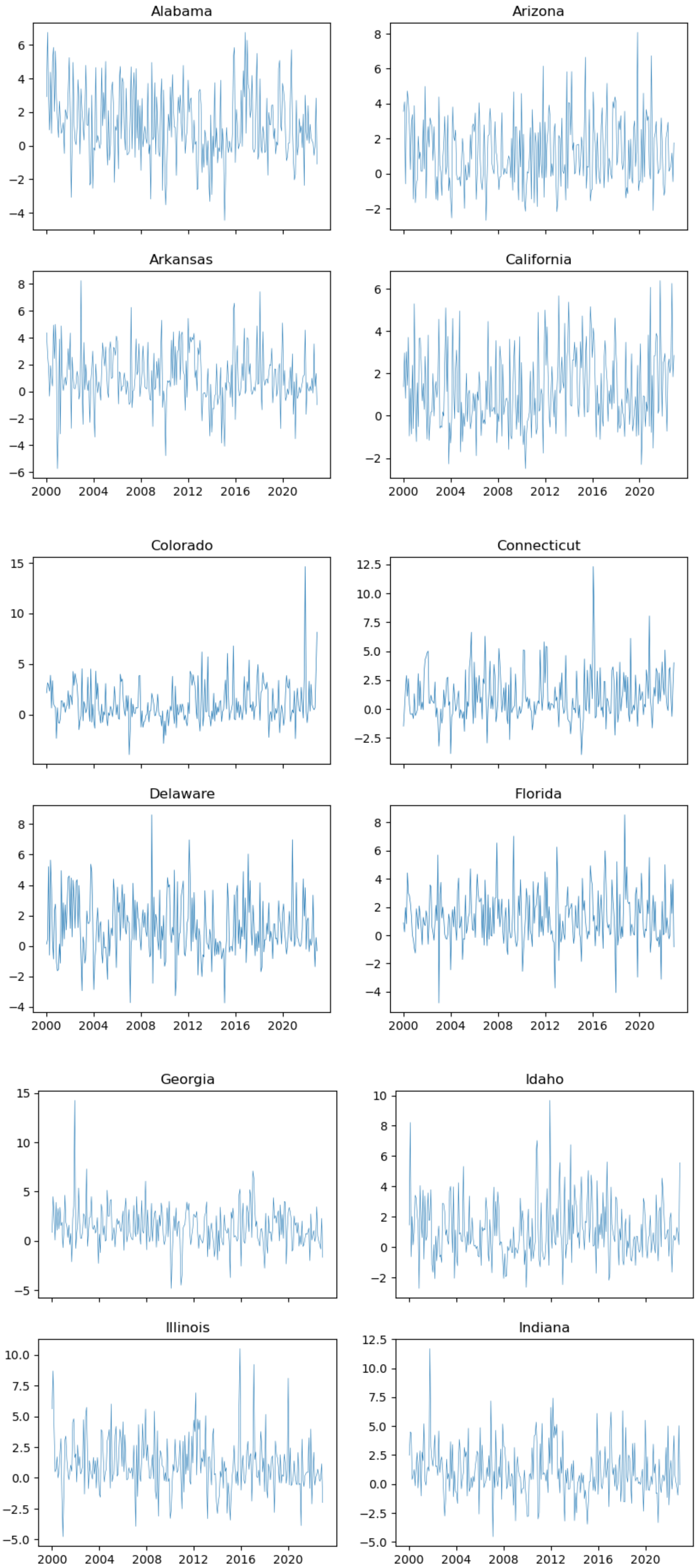
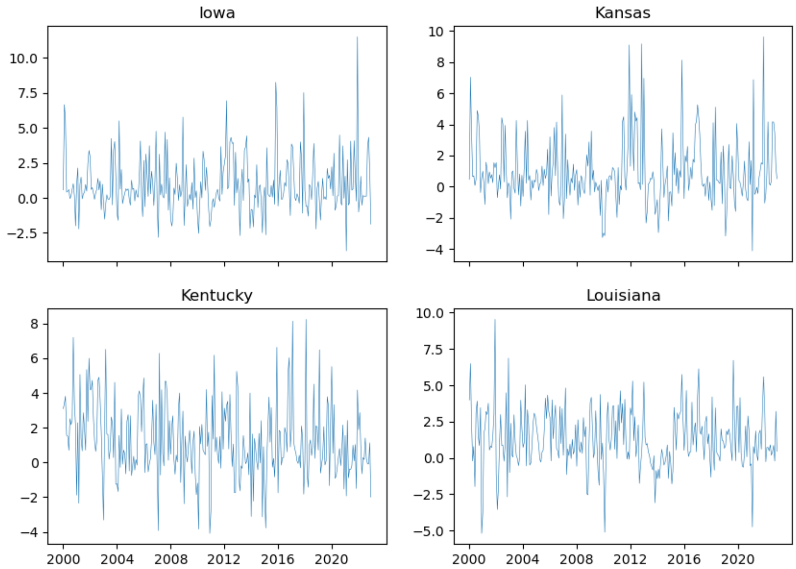
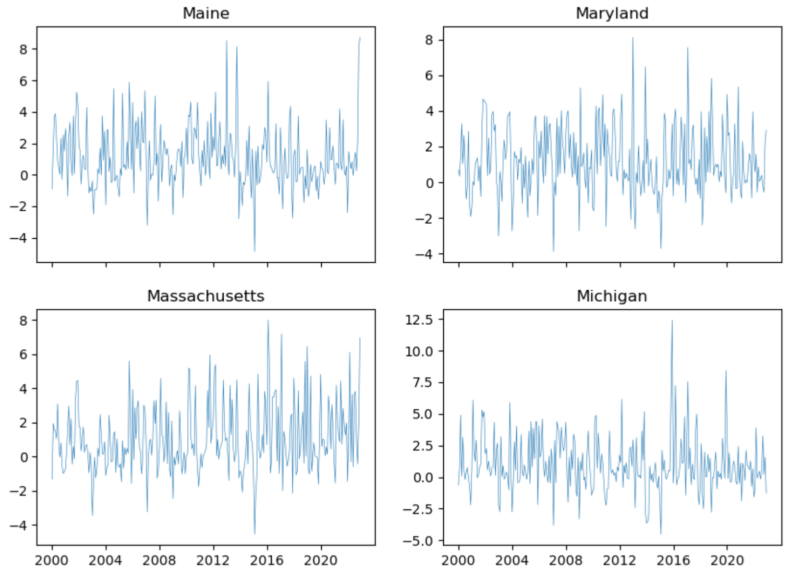
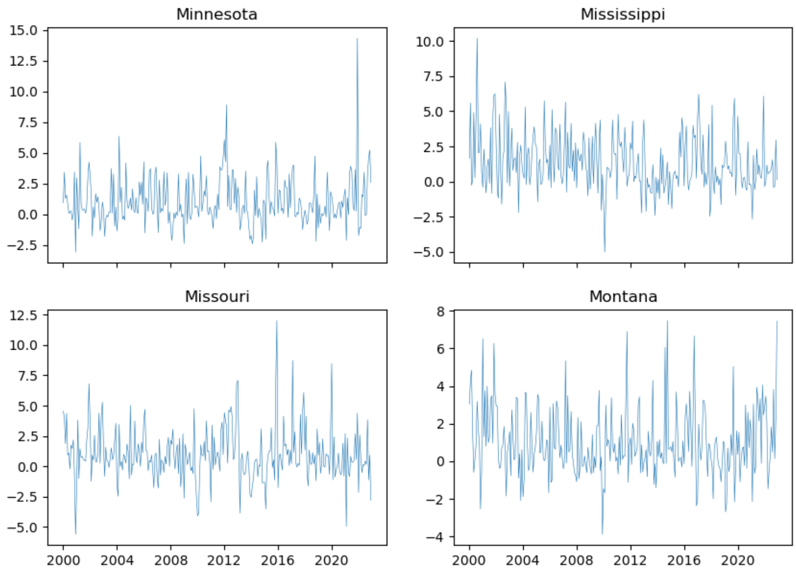


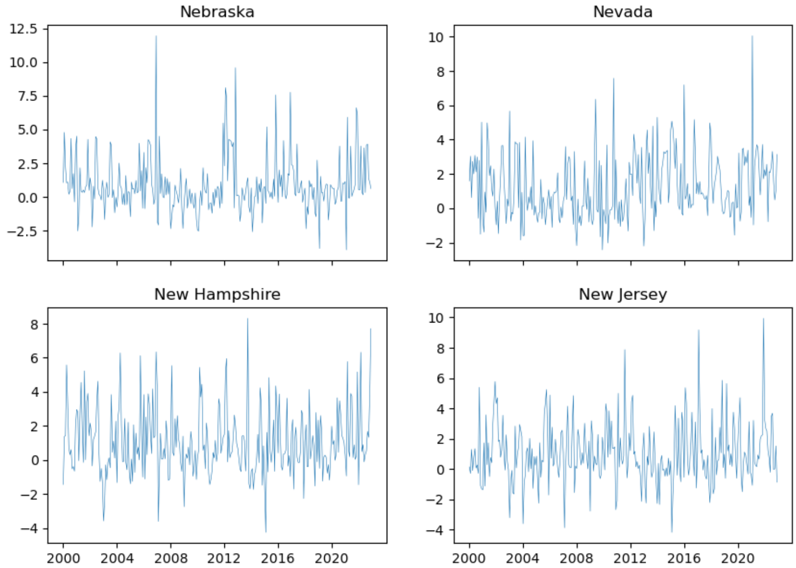
Figure 4: State-level Climate Disaster Index ($CLD_{s,t}$).

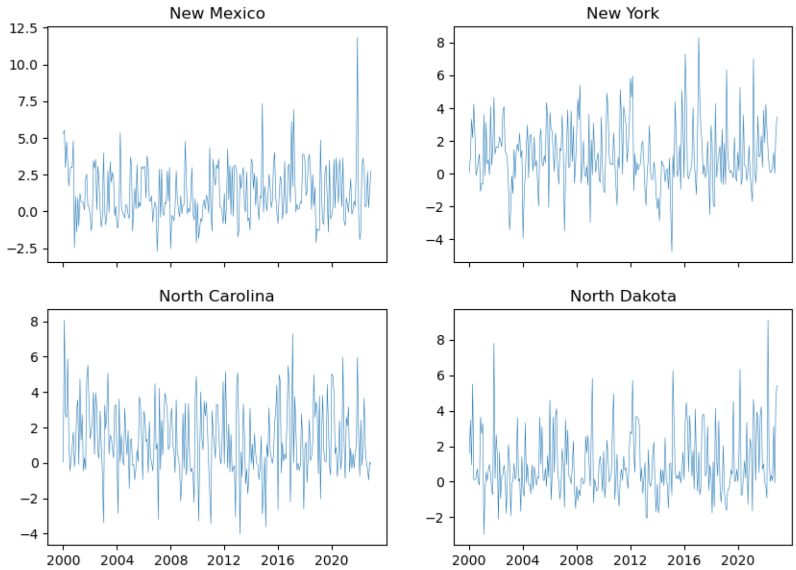


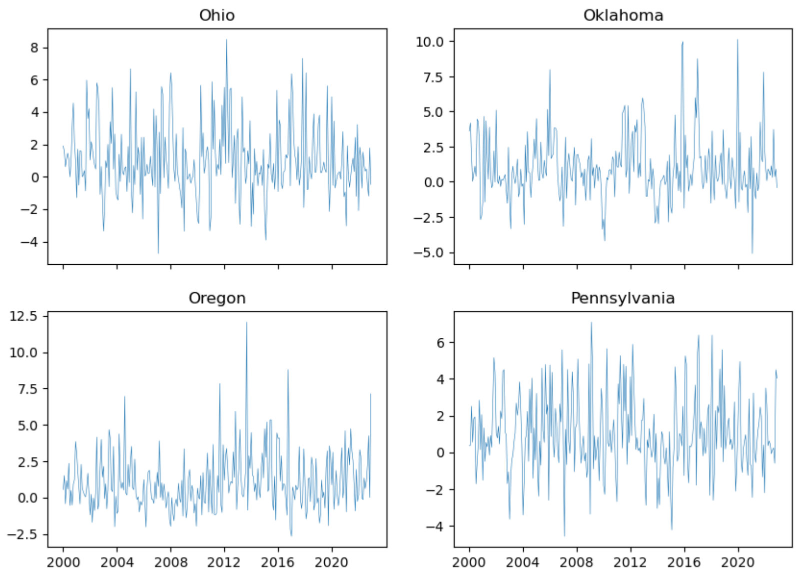

Iowa
10.0
7.5
5.0
2.5
0.0
−2.5
Kansas
10
8
6
4
2
0
−2
−4
Kentucky
8
6
4
2
0
−2
−4
2000
2004
2008
2012
2016
2020
Louisiana
10.0
7.5
5.0
2.5
0.0
−2.5
−5.0
2000
2004
2008
2012
2016
2020

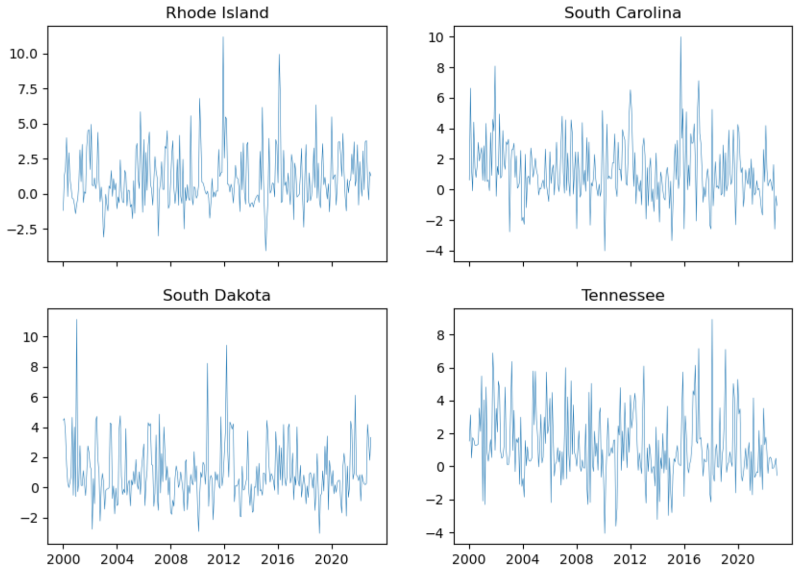

Maine
8
6
4
2
0
−2
−4
Maryland
8
6
4
2
0
−2
−4
Massachusetts
8
6
4
2
0
−2
−4
2000
2004
2008
2012
2016
2020
Michigan
12.5
10.0
7.5
5.0
2.5
0.0
−2.5
−5.0
2000
2004
2008
2012
2016
2020

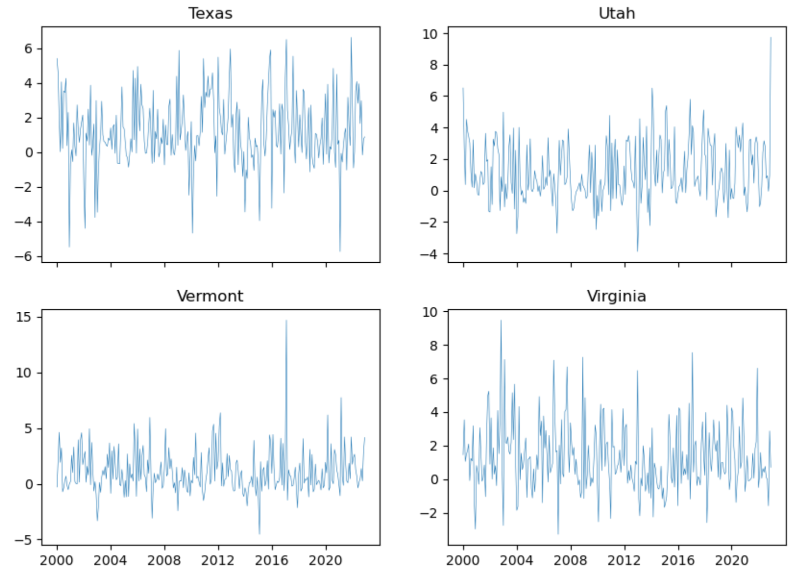

Minnesota
15.0
12.5
10.0
7.5
5.0
2.5
0.0
−2.5
Mississippi
10.0
7.5
5.0
2.5
0.0
−2.5
−5.0
Missouri
12.5
10.0
7.5
5.0
2.5
0.0
−2.5
−5.0
2000
2004
2008
2012
2016
2020
Montana
8
6
4
2
0
−2
−4
2000
2004
2008
2012
2016
2020

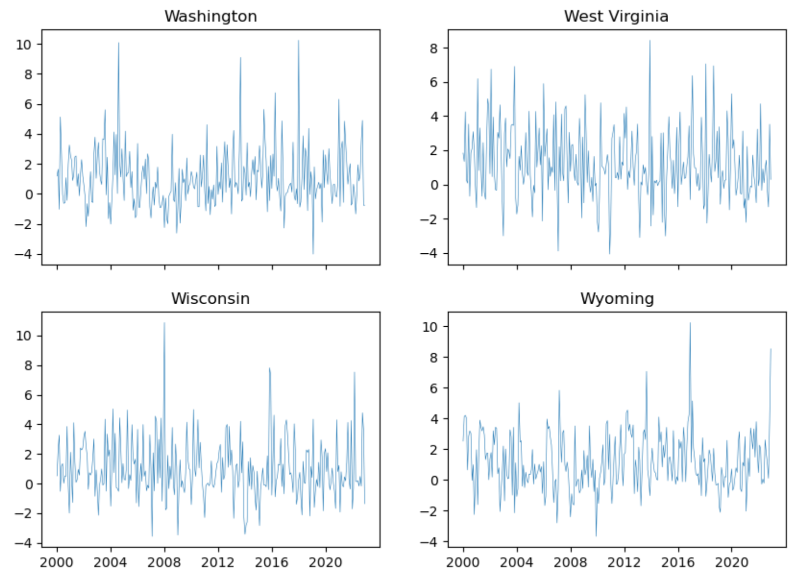

Nebraska
Nevada
New Hampshire
New Jersey


New Mexico
New York
North Carolina
North Dakota


Ohio
Oklahoma
Oregon
Pennsylvania


Rhode Island
South Carolina
South Dakota
Tennessee


Texas
Utah
Vermont
Virginia


Washington
West Virginia
Wisconsin
Wyoming