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Investor Concerns and the Pricing of Physical Climate Risk

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Abstract

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We study how global equity markets price the physical climate risk associated with tropical cyclones. To assess firms' exposure to this risk, we use a bottom-up, forward-looking measure of firms' expected losses to their geolocalized physical assets based on simulated cyclone tracks under different climate scenarios (RCP 2.6, 4.5, and 6.0). Throughout the sample period 2016-2022, we find no significant premium for tropical cyclone-related risks. But realized return may be affected by shifts in investors' concerns about physical risks. To measure these concerns, we use the search volume index (SVI) from Google Trends as the primary indicator, along with the global monthly occurrence of tropical cyclones for additional validation. We find that a one standard deviation higher exposure under RCP 4.5 is associated with a 1.05% higher annual returns during periods of low cyclone concern. However, during periods of heightened cyclone concern, a one standard deviation higher exposure is associated with a 2.31% lower annualized return. Overall, our results suggest that global equity markets have begun to price in the physical climate risk associated with tropical cyclones. However, during periods of increased cyclone activity, investor concerns may reduce demand for stocks that are more exposed to this risk, causing their prices to fall.

Keywords: Physical climate risks, stock returns, geolocalized physical assets, global ownership data, probabilistic disaster risk, climate risk pricing

JEL classification: G12; G23; G30; D62.

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1 Introduction

Intensifying climate change and associated natural disasters are already having negative socio-economic impacts in several countries around the world (IPCC, 2022). Over the past decade, weather-related events such as storms, floods, droughts, and wildfires have caused an average annual global economic loss of USD 235 billion, even reaching 291 billion in 2023. These economic impacts could become even more severe in the near future (Kotz et al., 2024; Waidelich et al., 2024). Losses could be amplified and have a global impact on our economies through several systemic mechanisms including interdependent and self-reinforcing climate shocks,[1] global supply chains, financial externalities and risk transfer (ECB/ESRB, 2023). Worldwide losses are projected to grow yearly by 5–7%, in line with actual loss increases over the last 30 years (Banerjee et al., 2024).

The increasing frequency and severity of extreme weather events has reduced the effectiveness of strategies to diversify, insure, or hedge against physical climate risks. In 2023, 62% of global losses from natural catastrophes were uninsured (Banerjee et al., 2024), highlighting a significant insurance coverage gap, even in Europe (EIOPA, 2023; ECB/ESRB, 2023).[2] From an investor's perspective, this persistent risk could negatively impact investments. Climate-related damages can drive up capital expenditures (CAPEX) and reduce margins or sales due to operational disruptions, significantly increasing downside risks for vulnerable firms (Bressan et al., 2024; Chen et al., 2024).

Standard asset-pricing theory suggests that investors should be compensated for holding assets that are more exposed to systemic risk, such as climate physical risk. However, empirical tests from the climate finance literature are somewhat inconclusive as to whether markets accurately price this type of risk (see, e.g., Sautner et al., 2023; Faccini et al., 2023; Braun et al., 2021; Nagar and Schoenfeld, 2022; Garbarino and Guin, 2021; Bressan et al., 2024; Acharya et al., 2023; Gostlow, 2021; Nguyen et al., 2022)[3]. One possible reason is that financial market participants may be influenced by behavioral biases and bounded rationality, leading to distorted risk perceptions (Choi et al., 2020; Alok et al., 2020; Dunz et al., 2021; Battiston et al., 2021). In addition, realized returns which are often used as a proxy for expected returns could be affected by unexpected shifts in investors' demands (Pástor et al., 2022). Finally, the complexities involved in estimating firms' climate risk exposure may also contribute to mispricing (UNEP-FI, 2021). Therefore, gaining a better understanding of how the market prices climate risks remains an area of great interest.

[1] such as heat waves and wildfires, floods and hurricanes for example

[2] The market of catastrophe (CAT) bonds, introduced in the early 1990s as a tool for transferring risk from insurers to investors, has grown rapidly over the past decade. However, the increase in climate-related disasters increases the risk of loss to investors and can lead to mispricing or underpricing of CAT bonds (Morana and Sbrana, 2019).

[3] see extended discussion of these results in the following section.

Tropical cyclones are among the world's most destructive natural disasters in terms of dollar losses, and the number of such events has doubled since 1980 (Hoeppe, 2016). With increasing intensity due to climate change, their global economic impact could reach USD 380 billion by 2050 (De Maximy et al., 2024). This paper therefore focuses on the risks associated with these events. We use a bottom-up forward-looking measure of risk (Bressan et al., 2024) that is based on a probabilistic assessment of damages to companies' physical assets. This measure is computed using the Climate Adaptation and Damage Assessment model (CLIMADA) (Aznar-Siguan and Bresch, 2019), an open-source risk assessment platform that is used to quantify the impacts of climate-related hazards such as tropical cyclones, floods, wildfires, and more. Specifically, we focus on two key measures: the average expected losses on physical assets due to tropical cyclones (referred to as the expected annual impact EAI) and the expected losses that would occur for rare events (referred to as the tail impact TI). We assess whether physical climate risk associated with tropical cyclones is priced by the equity market using the impact measures across three climate scenarios (RCP 2.6, 4.5, and 6.0). As an open-source risk assessment platform, the CLIMADA model allows users to define certain parameters or functions during the estimation process: not only the climate scenario can be freely chosen, but also the number of simulated cyclone tracks or the impact functions of cyclones. This flexibility enhances the estimation process and allows for a more comprehensive assessment of tropical cyclones risks.

Our analysis focuses on three highly exposed sectors (utilities, materials and energy) of the global equity markets over the period from 2016 to 2022. In our sample, more than 70% of firms have some exposure to tropical cyclones. The Utilities sector is the most exposed, with an expected damage (calculated as the probability of cyclone events multiplied by losses) of 0.15% across all firms in the year 2050 under the central climate scenario RCP 4.5, assuming a global warming of about 2.5°C over the century.[4] At first sight, this figure may seem relatively low but it hides significant variation across firms.[5] Moreover, not all cyclones are born equal. The average loss from the most severe cyclones is significantly larger, at 1.7% of firms' asset value (it is 1.4% and 1.2% for the Materials and Energy sectors respectively). In terms of country exposure, East Asia, the US and Central America are projected to be the most severely affected region in our sample, with some countries facing expected losses up to 16% of their firms' value if very severe cyclones occur). Although the European region is in general less exposed to tropical cyclone risk, European companies, such as those incorporated in France or the UK, with subsidiaries in high-cyclone-risk countries will not be spared.

Investors should be compensated for holding assets that are more exposed to sys-

[4]This figure represents the expected fraction of the total assets' value of firms that could be destroyed that year given simulated cyclone tracks taking into account the climate evolution.

[5]some firms have most of their assets located in high risk regions and could suffer losses as high as 30% of their facilities values in 1-in-50-year events.

temic risk, such as climate physical risk. However, throughout our sample period, we find no significant risk premium for tropical cyclone-related risks. This result is robust across different risk measures, whether it is the expected annual impact (EAI) or the tail impact (TI), and across different climate scenarios. Should we conclude that investors completely ignore tropical cyclone risks? Stock returns may also be influenced by shifts in investors' perception of these risks (Pástor et al., 2022). It is thus possible that over our sample periods, investors may have revised their assessment of the severity of physical risks, possibly due to heightened attention or increased media coverage. The premium associated with highly exposed stocks may be offset by the effect of increased investor concerns during periods of high cyclone activity, potentially leading to underperformance of highly exposed stocks.

To examine whether stock performance reflects investors' concerns, we analyse the relationship between stock returns, firms' cyclone exposure and measures of investors' concerns. We use two measures to capture these concerns: the global monthly occurrence of tropical cyclones and the worldwide Search Volume Index (SVI) on Google Trends. Our findings suggest that firms with higher cyclone exposure tend to earn higher returns when investor concerns are low. During these months, a one standard deviation increase in the expected annual impact (EAI) under RCP 4.5 is associated with a 1.05 percentage points increase in annualized returns. However, highly exposed stocks are likely to experience lower returns during periods of heightened cyclone concerns. A one standard deviation increase in cyclone exposure under RCP 4.5 is associated to a 2.31 percentage point reduction in annualized returns over these months. We observe similar results when using the unanticipated component of investors' concerns instead of the realized level. Overall, our analysis shows that investors' concerns about cyclone risks have a significant impact on stock performance.

Our paper is organized as follows. Section 2 presents a literature review on the pricing of physical risk exposure. Section 3 describes our data and physical risk estimates. Our results are described in section 4. Section 5 concludes.

2 Related literature

Our paper contributes to the growing literature on whether equity markets price climate physical risks. Recent studies rely on textual analysis of news, companies' annual reports, or call transcripts to build measures of climate risk exposure. Faccini et al. (2023) build climate change-related risk factors using textual and narrative analysis of climate change news. In particular, they classify climate risk factors into several categories including natural disasters and global warming. They find no significant risk premium for physical risk exposures. Nagar and Schoenfeld (2022) construct a climate change risk measure using firms' disclosure of weather risk and show a large positive and significant risk premium (between 2.2% and 3.5% per year, depending on the estimation method). Sautner et al. (2023) build a firm-specific climate change exposure measure from corporate earnings calls, capturing the attention to various climate topics (decomposed into opportunities, regulatory and physical shocks). They find no significant risk premium associated with physical risks, either when using realized monthly returns or forward-looking expected returns proxies from option prices.

Other studies employ historical weather data or model-based climate risk scores to extract physical risk premiums. Hong et al. (2019) use data from 31 countries with publicly listed equities in the food industry to measure and rank time trends in droughts across countries. They show that these trends can forecast the relative performance of food industry cash flows. These trends also forecast future stock returns, meaning that markets have not efficiently priced the information contained in droughts' trends. Bansal et al. (2016) use the change in K-year moving average temperature in the US and the standard set of 25 portfolios sorted on size and book-to-market ratios and ten industry portfolios to measure the impact of long-run temperature risk on equity prices and estimate the corresponding risk premium. They find a negative and significant market price for temperature risk. Using aggregate data of a long-term data set of storm losses provided by the Spatial Hazard Events and Losses Database for the U.S, Braun et al. (2021) construct an Aggregate Storm Loss Growth (ASLG) and use this time-series as a hurricane risk factor. Every month, they sort US stocks based on their sensitivity to this factor. They show that the portfolio of stocks reacting the most negatively to severe storm losses outperforms the portfolio of stocks reacting the most positively, with an excess return of 6.5% per year over 1995-2019. However, this risk premium is only significant among firms operating domestically (thus not globally diversified) and those geographically exposed to storm risk. The latter finding suggests that the market only prices the part of climate risk related to direct physical damage of facilities and ignores other financial losses originating from a deeper layer of economic linkages. Deghi et al. (2020) use across-country econometric analysis to determine whether aggregate equity valuations (price-to-earnings ratios of stock market indices) are sensitive to proxies for future changes in physical risk under various climate change scenarios. Overall, they find no evidence of equity valuation being negatively associated with projected losses, and also highlight the limited stock market reaction to natural disasters. The closest study to ours is Gostlow (2021) which uses Moody's 427 model-based climate risk scores for firms' exposure to physical climate risks to study whether international stock markets price climate change-related risks. 427 scores are constructed by aggregating facility-specific physical risk assessments to the firm level using corporate ownership mappings. The author documents a positive and significant risk premium for exposure to hurricanes (4.7% per year) and a negative and significant premium for exposure to heat stress (-7.1% per year).

In our paper, we use a transparent climate model-based measure, similar to the approach taken in Bressan et al. (2024). By applying this methodology to a sample of listed firms with activities in Mexico, the authors find that neglecting asset-level information can lead to underestimating investor losses by up to 70%, while neglecting acute risks can result in underestimations of up to 82%. Following the same methodology, we use the open-source CLIMADA model (Aznar-Siguan and Bresch, 2019) to estimate the average asset damage due to tropical cyclones. The assessment of damage to companies' facilities is forward looking for two main reasons. Firstly, based on historical tracks of cyclones and companies' facility locations, we can generate multiple synthetic cyclone tracks that are used to estimate the expected damage to facilities. Secondly, the model also allows for the consideration of climate change impacts under different climate scenarios (RCP 2.6, RCP 4.5, RCP 6.0) in the year 2050. Subsequently, we aggregate the projected asset-level damage to the company level, taking into account the weights of each asset value in the companies' total physical assets. Throughout the sample period (2016 - 2022), we find no significant risk premium for tropical cyclone-related risks.

Our paper also contribute to the literature on investors' attention to information and its implication on the market. Many studies have shown evidence that investors have limited attention to information (See, for example, Barber and Odean, 2008; DellaVigna and Pollet, 2007, 2009; Hirshleifer et al., 2009 and the survey by Gabaix, 2019 for a more profound review).

Related to climate risk, Alok et al. (2020) find that fund managers located within major disaster regions tend to display an aversion to disaster zone stocks compared to managers located in distant regions. Consistent with the concept of salience bias, such aversion tend to fade away over subsequent quarters following the disaster.

Other studies show more direct evidence on the impact of investors' concerns or attention on the financial market. Choi et al. (2020) using Google search volume as a proxy for public attention to climate change, show that there is an increase in attention when the local temperature is abnormally high. Importantly, this increased attention can have an impact on the equity market. They show that carbon-intensive stocks tend to earn lower returns than other stocks when the temperature in the cities where the exchanges are located is abnormally high. This can be attributed to investors revising their beliefs about the impact of climate change during such periods, leading to a decrease in demand for carbon-intensive stocks. The study also shows that retail investors tend to reduce their holding of high-emission firms when facing abnormally warm weather. However, there is no evidence of such behavior among institutional investors. On the contrary, blockholders seem to increase their holdings when the local temperature is high. Pástor et al. (2022), on the other hand, examine the role of environment concerns in the performance of green versus brown assets on the stock and bond markets. Their findings provide evidence that green assets have higher realized returns compared to brown assets. This outperformance is shown to reflect the unexpected shocks in environment concerns, proxied by the Media Climate Change Concern index (MCCC) constructed by Ardia et al. (2023). Furthermore, Ardia et al. (2023) also observe that green stock prices tend to increase during days with high climate change concerns, as measured by the MCCC index. They show that such impacts can be attributed to both concerns about transition and physical risk. The study also shows that the unexpected positive shock in climate change concerns is associated with an increase in the discount rate for brown firms and a decrease in the discount rate for green firms. This finding provides evidence for investors' time-varying perceived climate risk, which is driven by their concerns or attention to the issues. Leippold and Yu (2023), on the other hand, show that the increased attention to green innovation in the recent period has raised demand for stocks of green innovative firms and results in higher performance for these stocks compared to their less green innovative counterparts. Overall, these studies suggest that environmental concerns and public attention to climate change-related issues can have significant effects on the performance and valuation of green and brown assets.

In this paper, we examine the impact of investors' concerns related to tropical cyclone events on stock performance of firms with different level of exposure. To measure cyclone concerns, we use the search volume index (SVI) from Google Trends as our primary indicator, along with the global monthly occurrence of tropical cyclones for additional validation. We show that firms with high exposure to cyclones tend to outperform those with low exposure when investors' cyclone concerns are low. In contrast, these firms are more likely to underperform during periods of increased concerns. Our paper provides evidence on the influence of time-varying perceived climate risk, driven by investors' attention or concerns to the risk, on stock performance.

3 Data and Methodology

3.1 Firm-level physical risk estimates

The CLIMADA model utilizes two main data inputs: historical cyclone tracks and companies' facility locations. To obtain the historical cyclone tracks, we rely on the International Best Track Archive for Climate Stewardship (IBTrACS) dataset, which provides tracks of cyclones from all basins since 1851, along with information on their intensity. [6] However, for our analysis, we focus on the more recent period between 1950 and

[6] https://www.ncei.noaa.gov/products/international-best-track-archive

2021. Regarding the companies' facility locations, we use a snapshot from the year 2021, which was kindly provided by the authors in Bressan et al. (2024). For each physical asset, we construct a measure of physical climate risks by focusing on hazards from tropical cyclones, using the approach in Bressan et al., 2024. Our measure of firms' exposure is based on the probabilistic climate acute risk assessment of damages caused by cyclones, at the level of their physical assets, using the CLIMate ADApt (CLIMADA) model (Aznar-Siguan and Bresch, 2019; Bresch and Aznar-Siguan, 2021; Aznar-Siguan et al., 2022), expected in the year 2050 for three Representative Concentration Pathways (RCP) scenarios (2.6, 4.5, 6.0).[7] It is important to note that throughout this paper, we assume that the asset locations remain constant over the entire sample period, which also implies a fixed physical risk measure across time for each company.

The asset locations dataset consists of all companies that can be identified as owners of productive facilities. The dataset comprises different types of facilities including mines and mining processing facilities, power plant units, oil refineries, LNG liquefaction and regasification plants, and steel and cement plants (for further explanations, please refer to Bressan et al., 2024). We then reconstruct ownership chains for each asset. The choice of asset types is conditioned by data availability. As our asset ownership chains are limited to some types of physical assets such as mines, power plants, oil refineries, etc., it is reasonable to focus our analysis on certain industrial sectors in which these assets are crucial for their economic activities. Therefore, we narrow down our sample to firms operating in the Energy, Materials, and Utilities sectors. This decision is supported by Hain et al. (2022) who shows that companies in these three sectors are indeed the most exposed to physical risks. Our sample include 965 companies and 29,725 assets. The assets' distribution is represented in Figure 1, from which we can see that the most represented assets are power plant units (with 24,201 assets), followed by mines and mining processing facilities (4,508 assets).

[Figure 1 here.]

Figure 2 illustrates the geographic distribution of assets in the dataset, with different colors representing different asset types. The plot suggests that assets are not evenly distributed across the world, with a high concentration of mining facilities in regions such as the western coast of the Americas and Australia, and power plant facilities in Europe, the eastern coast of the U.S., and East Asia.

[Figure 2 here.]

[7] RCPs describe different pathways of greenhouse gas concentrations in the atmosphere over time. RCP2.6 is the most optimistic scenario, where we take strong action to reduce emissions and the world keeps global warming below 2°C. In scenario RCP4.5, emissions peak around 2040 then decline, resulting in a warming about 2.5°C by 2100. RCP6.0 assumes rising emissions until 2080, leading to around 3°C of warming by 2100.

Next, based on each historical event on IBTrACS, we generate additional 30 synthetic tracks using a random track generator and the wind field model proposed by Holland (2008). These synthetic tracks are essential for the probabilistic assessment of cyclone impact conducted later, ensuring that our measure is not solely dependent on historical data. After removing any duplicated tropical cyclone tracks, we are left with a total of 138,849 cyclones (including both historical and simulated tracks). We map these tracks to a global grid of centroids, and perturb the tracks of tropical cyclones to account for changes in tropical cyclones' intensities and frequencies caused by climate change impacts.[8] To account for the potential impact of climate change, CLIMADA uses the results obtained by Knutson et al. (2015) and applies linear interpolation for various RCP scenarios. Our analysis focuses on the expected impact for the year 2050.

For each asset in our dataset, we identify the nearest centroid on the global grid of centroids and compute the wind speed in a given scenario. Then, we estimate the damages from wind to each asset using the damage function from Emanuel (2011). In the functional specification in Emanuel (2011), damages vary as the cube of wind speed over a threshold value; the percentage change of damaged property approaches unity at very high wind speeds but never exceeds unity.[9]

$$D_{frac} = \frac{v^3}{1+v^3}, \tag{1}$$

where

$$v = \frac{max((W_{speed} - W_{threshold}), 0)}{W_{half} - W_{threshold}}, \tag{2}$$

Equations 1 and 2 translate wind speed into a fraction of damaged property (D_{frac}) given the two values $W_{threshold}$ (i.e. the wind speed below which no damages occur) and W_{half} (i.e. the wind speed at which half of the property value is destroyed). Following Bressan et al. (2024), we apply a uniform damage function across all asset types due to the unavailability of data needed to calibrate the function for each specific asset type and geographic region. For each physical asset and each event (both historical and synthetic), we compute the fraction of the asset's value that is destroyed. Then we translate the ratio of damaged property into impact (i.e. direct damages; $x_{i,j,s}$) by multiplying it by the asset's exposed value.[10]

To obtain our physical risk metric, we first compute expected annual impact (EAI)

[8] We have a global grid resolution of 0.5 degrees longitude/latitude, and a total of 204,043 centroids.

[9] Damage function in Equation 1 considers only wind speed and does not consider damages from storm surge and rainfall. Although a common assumption in the literature (Emanuel, 2011; Aznar-Siguan and Bresch, 2019), it can lead to underestimation of damages in cases of less windy storms Aznar-Siguan and Bresch (2019). Additionally, we do not account for adaptation measures in the damage function, as company-level data about adaptation efforts is not easily accessible.

[10] We do not scale the asset value to 2050, which does not represent an issue because we use relative damages as the independent variable in our regression specification (please see Equation 4); if the value of an asset increased/decreased over time, damages would increase/decrease accordingly, but the relative damages would remain the same.

for each physical asset j, in each RCP scenario s, in the year 2050. EAI_{js} is computed as Aznar-Siguan and Bresch (2019):

$$EAI_{js} = \sum_{i=1}^{N_{ev}} x_{ijs} F(E_i), \tag{3}$$

where X is the impact random variable and x_{ijs} its realization. E_i is an event, F its annual frequency, and N_{ev} is the number of events (both historical and synthetic) considered. Events are assumed to be independent. EAI thus measures average acute risk on physical assets.

Second, we also measure tail risk, by computing 3 measures of tail impact (TI) for each scenario, estimating the expected losses on physical assets that would occur for rare cyclone events. Acute tail risks are specified in terms of return periods (e.g. a 100-year event indicates a value of losses not exceeded with probability 0.99, or a 0.99-quantile).[11]. Return periods are thus equivalent to percentiles of the loss distribution. Accordingly, the return period of an impact is computed as the inverse cumulative probability of an impact of a given magnitude or stronger to occur. For instance, if a tropical cyclone of a certain category is an RP50 tropical cyclone in a given location, that means that over the next century, a tropical cyclone of that category or stronger is expected to pass within 58 miles of that location twice.

Figure 3 show the asset-level damage caused by an RP100 event under the scenario RCP 4.5. The plot highlights the exposure of facilities to tropical cyclones in the most vulnerable regions, including the Eastern Coast of the U.S., Central America, and East Asia.

[Figure 3 here.]

Our measure of companies' exposure to tail risk is the level of damage exceeded at a fixed low annual frequency of 1/50, 1/100, 1/250, or equivalently the damage from tropical cyclones corresponding to the return period of 50, 100, and 250 years respectively, in a given scenario (i.e. RCP 2.6, 4.5, and 6.0), expressed as a percentage of the total value of company's physical assets.

We then aggregate the projected damage at the asset-level to the company-level taking into account the weights of each asset value in the companies' total physical assets. Figure 4 shows the sector-level distribution of firms in the sample. Out of 965 firms in the final sample, 66% (636 firms) are in the Materials sector, 20% (191 firms) are in the Utilities sector and 14% (138 firms) are in the Energy sector.

[Figure 4 here.]

[11] Return periods of tropical cyclones are defined as "the frequency at which a certain intensity of hurricanes can be expected within a given distance of a given location". See `https://www.nhc.noaa.gov/climo`

In our sample, more than 75% of firms have some exposure to tropical cyclones. As shown in Panel A of Table 1, there is a large variation in EAI and TI across sectors. The Utilities sector is the most exposed to tropical cyclones with an average EAI (under scenario RCP 4.5) of 0.14% (TI of 1.80 % for a return period 50 years, under scenario RCP 4.5).[12] The Materials and Energy sector has an average EAI of 0.11% and 0.09% (TI of 1.44% and 1.47%, respectively for a return period 50 years and under scenario RCP 4.5) . There is also a significant variation within each sector. For example, in the Materials sector, on average, the firm at the 20th percentile has 0% of its facilities destroyed by a one-in-50 years cyclone event while the firm at the 80th percentile has about 1.14% of its facilities destroyed.

[Table 1 here.]

Figure 5 shows the distribution of firms by country of incorporation. The country with the largest number of firms in the sample is Canada with 244 firms (25%), followed by the United States with 150 firms (16%). Panel B of Table 1 presents twenty countries of incorporation that are most exposed to tropical cyclones. Countries with firms having the highest exposure include Taiwan, the Philippines, and Japan with average EAI of 2.11%, 1.05% and 0.66% (in scenario RCP 4.5). This also holds for the TI measures. On the other end of the spectrum, thanks to their geographical locations, many countries (about 25%) have almost no exposure to tropical cyclone risks regardless of the measures and scenarios.

[Figure 5 here.]

Panel A of Table 2 shows the summary statistics of the firms' exposure to cyclones. In the climate scenario RCP 4.5, the average firm in the sample has an EAI of 0.11% and a TI of 1.52%, 1.95%, and 2.63% for the three return periods of 50, 100, and 250 years. Notice the damage in dollars of rare events is largest for an event of the 250-year return period, followed by the return period of 100 years, and finally the return period of 50 years. It is also shown in table 5, that the correlations between EAI and TI in different RCP scenarios are all above 0.80, suggesting that exposure to cyclones is mainly driven by the locations of facilities.

3.2 Concerns about Cyclone Risk

Our primary measure of concern about tropical cyclone risk is based on public interest in the topic "Tropical Cyclone" using Google Trends. We collected the search volume index (SVI), which ranges from 1 to 100, for Google News searches with a worldwide scope. The monthly SVI likely captures both the frequency and severity of tropical

[12] An average EAI of 0.15% means an average expected annual loss of 0.15% of firms' physical assets

cyclone events, i.e., public attention, as measured by SVI, tends to increase not only during months with a higher number of cyclone occurrences but also in response to cyclones that cause significant damage. Similarly, sudden changes in SVI could reflect unexpected shifts in the frequency and intensity of cyclones, potentially driven by climate impacts. In the following analysis, we use the natural logarithm of the index. Figure 6 displays the monthly SVI, revealing a seasonal pattern, with a clear peak around September each year.

For robustness, we also use the monthly count of global cyclone events recorded in the EM-DAT (Emergency Events Database) [13] as an alternative measure of concern about tropical cyclones. This comprehensive global database tracks detailed information on natural disasters, including earthquakes, floods, hurricanes, droughts, and more. EM-DAT provides unbiased data starting from January 2000. We filter the data to include only events categorized as "Tropical Cyclone" or "Storm (General)". Since disaster events typically span several days or weeks, we attribute each event to the month in which it begins and remove any duplicate records. Figure A1 shows the monthly count of cyclone events worldwide, which, like the SVI, displays a seasonal peak around September. Notably, the high correlation (0.58) between the two time series suggests that public interest aligns with periods of intense cyclone activity.

3.3 Financial data

We merge firm-level physical damage data with financial data retrieved from Compustat for the period 2016-2022 using ISIN identifier. Although firm-level exposures to tropical cyclones can vary over time, our measure is static, as it is based on a snapshot of facility locations from the year 2021 due to limited data access. Therefore, we focus our analysis on the most recent period, starting from the adoption of the Paris Agreement in December 2015. The matching produces 81,149 firm-month observations on 965 unique firms incorporated in 64 countries.

We obtain price data from Compustat North America and Compustat Global. The total returns are computed by adjusting for stock splits and the distribution of dividends. The monthly risk-free rate is obtained from Kenneth French's data library. The excess return is the difference between the monthly returns and the risk-free rate. Our sample spans the period from January 2016 to December 2022. Excess return is winsorized at 1% level to eliminate the impact of outliers.

We also retrieve from Compustat accounting data including number of share outstanding, book value of equity, long-term debt, capital expenditure, net income, property, plant and equipment, at a quarterly frequency. For firms whose reporting currencies are not US dollars, we first convert their accounting figures into US dollars using

[13] https://public.emdat.be/

the monthly exchange rate provided by Compustat.

3.4 Empirical strategy

We begin by examining the climate physical risk premium in the cross-section of stocks. For this purpose, we estimate the following regression model:

$$RET_{i,t} = \alpha_0 + \alpha_1 EXPOSURE_i + \alpha_2 Controls_{i,t} + \delta_{industry} + \delta_{country} + \delta_t + \epsilon_{i,t} \quad (4)$$

The dependent variable $RET_{i,t}$ is the monthly stock return for firm i in month-year t. In our main analyses, the explanatory variable $EXPOSURE_i$ is the Expected Annual Impact (EAI) in each of the three representative concentration pathways 2.6, 4.5, and 6.0. In some analyses, we also use TI for each of the three return periods 50, 100, and 250 years, and in each of the three representative concentration pathways RCP 2.6, RCP 4.5, and RCP 6.0 as a measure of exposure to cyclones.

We control for usual firms' characteristics that may influence stock returns. Our control variables are defined as follows. $LOGSIZE_{i,t}$ is the natural logarithm of company market capitalization in US dollars, computed as the product of closing price and number of shares outstanding at the end of the month. $B/M_{i,t}$ is the book-to-market ratio computed by dividing the book value of equity at the end of each quarter by the market capitalization at the end of each month. $LEVERAGE_{i,t}$ equals the long-term debts divided by the book value of equity, both measured at the end of each quarter. $INVEST/A_{i,t}$ is the end-of-year capital expenditure divided by the book equity of asset at the end of each quarter. $ROE_{i,t}$ is the return on equity, computed by the net income divided by the book value of equity, at the end of the quarter.[14] $LOGPPE_{i,t}$ is the natural logarithm of companies' property, plants, and equipment at the end of the quarter. $MOM_{i,t}$ is the average of the most recent 12 months' stock returns (from $t-12$ to $t-1$) on stock i. $VOL_{i,t}$ is the standard deviation computed using the most recent 12 months' stock returns. To eliminate the impact of outliers, we winsorize B/M, LEVERAGE, INVEST/A, and ROE at 2.5% level and MOM and VOL at 0.5% level following Bolton and Kacperczyk (2021).

In all of our regressions, we include fixed effects for the country of incorporation and the month-year ($\delta_{country}$ and δ_t, respectively). Given that exposure to physical risks is primarily determined by the location of facilities, which may vary across industries, we also control for industry fixed effects ($\delta_{industry}$) in our main specifications. Standard errors are clustered at the firm level.

[14] When quarterly net income is unavailable, such as in the case of firms incorporated in Japan, we use end-of-year net income divided by four as quarterly income.

4 Results

4.1 Exposure to cyclones and stock returns

Table 4 reports the coefficients on EAI for the full sample period from January 2016 to December 2022. We show the results without (columns 1 to 3) and with industry fixed effect (columns 4 to 6). The estimated coefficients are small in magnitude and statistically insignificant in all columns, suggesting that investors generally do not significantly price exposure to tropical cyclones. The magnitudes of the estimated coefficients are very similar under different RCP scenarios.

[Table 4 here.]

We conducted the same analysis using TI to assess exposures to tail risks, and the results are presented in Table 5. Across all scenarios and return periods, we no statistically significant premiums associated with exposure to tail risks.

[Table 5 here.]

4.2 Investors' concerns about cyclone activity

Based on the analysis in the previous section, one may conclude that the market does not price cyclone-related climate risks. Theoretically, firms with greater exposure to physical risks should yield higher returns than those with lower exposure. However, stock returns may also be influenced by shifts in investor perception of these risks in short or medium terms. If investors revise their assessment of the severity of physical risks over our sample period (for example due to higher attention, increased media coverage, etc.), the premium for high risk companies might be offset by the effect of investors' unanticipated increase in global physical risks concerns, leading to an underperformance of highly exposed stocks during the period of interest. A similar dynamic has been identified in several papers on climate change, where investors may revise their beliefs in response to extreme weather events, such as unusually high temperatures Choi et al. (2020), increased physical risks activity like cyclones, floods, etc. (Alok et al., 2020; Giglio et al., 2021), or in response to heightened media coverage on climate issues (Pástor et al., 2022). For example, (Pástor et al., 2022) observe that the strong increase in climate concerns over the last decade has led to the ex post outperformance of green stocks. This outperformance observed in realized returns cancels out the (ex ante) positive premium typically expected for brown stocks. Similarly, in our case, periods of intensified cyclone activity could raise investor concerns and reduce demand for stocks that are more exposed to such risks. This reduced demand can lead to a decline in the price of these stocks, even if the cyclone events do not directly impact the firms' assets.

To examine whether stock performance reflects investors' concerns, we analyze the relationship between stock returns, firms' cyclone exposure and measures of investors' concerns about cyclone risks. As a proxy for concerns about tropical cyclones, we use the search volume index (SVI) for "Tropical cyclone" on Google Trends with location set to worldwide.[15] [16] As the worldwide SVI is not directly linked to the local damage suffered by a particular company at the facility level, these measures are more likely to capture the heightened investor awareness of cyclone risks among investors than the actual localized damage.

We estimate the following equation:

$$
\begin{aligned}
RET_{i,t} = \alpha_0 + \alpha_1 EXPOSURE_i + \alpha_2 EXPOSURE_i \times CONCERNS \\
+\alpha_3 Controls_{i,t} + \alpha_4 Controls_{i,t} \times CONCERNS \\
+\delta_{industry} + \delta_{country} + \delta_t + \epsilon_{i,t}
\end{aligned}
\tag{5}
$$

where $CONCERNS$ is the measure for investor concerns about tropical cyclone risks. In Table 6, we use the worldwide Google Search Volume Index (SVI) as a proxy for $CONCERNS$. In table A1 in the appendix, we use the monthly count of cyclone events recorded in the EM-DAT database ($CYC.EVENTS$) as an alternative measure. We expect α_1 to be positive, indicating that firms with higher exposure to cyclones should earn higher returns when cyclone concerns are low, and α_2 to be negative, meaning that highly exposed stocks are more likely to suffer from an increase in cyclone concerns.

[Table 6 here.]

Table 6 shows the coefficients α_1 and α_2 estimated from model 5. In columns 1-3, we use the natural logarithm of Google SVI (SVI) as a measure for concerns. Under all climate scenarios, the estimated coefficient α_1 is positive and statistically significant, implying a higher return for highly exposed firms when investor concerns about tropical cyclone are low. This effect is also economically important. For example, one standard deviation increase in exposure to cyclones in the climate scenario RCP 4.5 is compensated with a 0.16 percentage points higher (0.39×0.413) monthly stock return (1.94 percentage points higher annualized returns). Conversely, the negative and significant coefficients on the interaction terms indicate that stock performance deteriorates with rising investor concerns, particularly for firms with high exposure. Specifically, a unit increase in SVI under RCP 4.5, combined with a one standard deviation higher exposure

[15] We download the search volume index (range 1-100) for Google news search of "Tropical cyclone" as a disaster type (topic).

[16] Alternative proxies for investors' concerns about global cyclone activity could include measures of media attention, as in Pástor et al. (2022). However, unlike global climate change concerns, we are not aware of publicly available measures of media attention specifically focused on cyclones.

to cyclones, results in a 0.12 percentage point decrease in monthly returns (equivalent to a 1.43 percentage point decrease in annualized returns).

In Columns 4-6 of table 6, to ease the interpretation, we instead use a binary indicators to measure high investor concerns: $HIGH.SVI$, which equals 1 if the SVI for the current month is above the median and O otherwise. As in the first three columns, firms with higher cyclone exposure tend to earn higher returns when investor concerns are low. Specifically, a one standard deviation increase in EAI under RCP 4.5 is associated with an increase of 0.09 percentage points in monthly returns (1.05 percentage points in annual returns). However, the combined effects of exposure (the sum of $\alpha_1 + \alpha_2$) are negative across all specifications, confirming that stocks of highly exposed firms are more adversely affected when investor concerns are high. A one standard deviation increase in exposure to cyclones under RCP 4.5 is associated to a decline of 0.19 percentage points in monthly returns, which translates to a 2.31 percentage point decrease in annualized returns. [17]

As a robustness check, Table A1 in the appendix uses the monthly number of tropical cyclone events as an alternative measure of investor concerns about cyclones. Columns 1-3 use the actual number of cyclone events ($NO.EVENTS$), while columns 4-6 use a binary indicator that equals 1 if $NO.EVENTS$ exceeds the median value during the sample period. Consistent with the findings in Table 6, the estimated coefficient α_1 is positive across all scenarios (statistically significant in columns 1-3), indicating higher returns for firms with greater exposure when investor concerns about cyclones are low. For instance, under the RCP 4.5 climate scenario and when concerns are low, a one standard deviation increase in EAI is associated with a 0.07 percentage point increase in monthly returns (equivalent to a 0.79 percentage point increase in annual returns). The lack of significance in columns 4-6 may be attributed to the fact that while SVI are likely to capture public attention driven by both the frequency and intensity of tropical cyclones, $NO.EVENTS$ only serves as a proxy for concerns related to cyclone frequency. Columns 4-6 show the combined negative effects of exposure ($\alpha_1 + \alpha_2$), indicating that stocks of highly exposed firms are more adversely affected when investor concerns are elevated. Specifically, a one standard deviation increase in cyclone exposure under RCP 4.5 leads to a 0.22 percentage point decline in monthly returns, which translates to a 2.69 percentage point decrease in annualized returns.

Given the seasonality of tropical cyclones, one could argue that the heightened concerns about cyclones observed in certain months of the year due to increased cyclone activity may have been partially anticipated by investors based on past observed cyclone events. Therefore, these concerns may not have been entirely surprising. In the

[17] Note that the negative returns observed for highly exposed firms during periods of high cyclone concerns could be due not only to increased investor attention, but also to the fact that, at least for hurricane-affected firms, investors receive new information about firms' cash flow losses due to unexpected physical disasters.

following analysis, we will focus on the "unexpected" component of investors' concerns and examine whether this component negatively impacts the realized returns of firms that are highly exposed to cyclones. We thus isolate the shock component of these concerns ($SVI.SHOCK$), calculated as the realized value (of SVI) in the current month and the month-m historical mean computed using data up to the same month in the previous year.[18]. We then perform similar analysis as in the previous regressions (see equation 5), incorporating the interaction of firms' cyclone exposure with the "shock" components of investors' concerns while also controlling for the anticipated component ($SVI.EXP$).

Table 7 presents the results of this analysis, which are consistent with those reported in Tables 6 and A1. Generally, the coefficients on firms' exposure to cyclones are positive, indicating that firms with higher exposure might have higher returns when shocks to investors' concerns about cyclones are low. However, the coefficients are statistically insignificant. The estimated coefficients for the interaction between cyclone exposure and the shock to concerns are all negative and statistically significant, suggesting that highly exposed firms are more adversely affected when there is an unexpected shock to cyclone concerns. Similarly, for a unit shock in the SVI, a one standard deviation increase in exposure under the scenario RCP 4.5 results in a 0.18 percentage point decrease in monthly returns [19]. Our findings align with previous evidence showing that strong investor concerns about climate issues are associated with the underperformance of stocks that are highly exposed to these issues. (Pástor et al., 2022; Ardia et al., 2023; Choi et al., 2020).

[Table 7 here.]

As a robustness check, we replicate the analysis using shocks to the number of cyclone events, denoted as $NO.EVENT.SHOCK$. Similar to $SVI.SHOCK$, $NO.EVENT.SHOCK$ is calculated as the difference between the actual number of cyclone events in the current month and the historical mean for the same month, using data up to the previous year.[20] The results are consistent with those in Table 7, indicating that highly exposed firms tend to perform better when the unanticipated change in cyclone events is low, but suffer more when this shock is high.

[18] Data for Google SVI starts from January 2008

[19] We also forecast investors' concerns using three different methods: the values from the same month in the previous year, the values from the previous month, and the predicted values from the $SARIMA(0,0,0)(1,0,0)_{12}$ model, which was estimated using data from January 2000 up to the month before our analysis. The results are very similar; specifically, we find that firms with high exposure to cyclones are more negatively impacted when there is an unexpected (positive) shock to cyclone concerns.

[20] Data for the number of cyclone events is available starting from January 2000.

5 Conclusion

In this paper, we use a bottom-up, forward-looking measure of cyclone risk exposure based on the probabilistic assessments of damages to companies' physical assets (Bressan et al., 2024). We estimate the average expected losses on physical assets due to cyclones (expected annual impact, EAI) and the expected losses that would occur for rare hurricane events (tail impact, TI) in three different climate scenarios (ECP 2.6, 4.5, and 6.0) for the year 2050.

We first study whether physical climate risks associated with tropical cyclones are priced by the equity market during the recent period from 2016 to 2022. Throughout this period, we find no significant premium for tropical cyclone-related risks. Considering that the observed risk premium in the sample period could be potentially affected by the shifts in investors' concerns about physical risks, we use two measures to capture cyclone concerns: the global monthly occurrence of tropical cyclone events and the worldwide search volume index (SVI) on Google Trends. Our findings show that firms with higher cyclone exposure tend to earn higher returns when investor concerns are low. Conversely, these firms are likely to experience lower returns during periods of heightened cyclone concerns.

These results highlight how investors adjust their expectations regarding the impact of climate change. Despite widespread recognition that climate change can amplify both the intensity and frequency of cyclone activity, investors appear to either overlook this information or incorporate it insufficiently when valuing assets. When cyclones occur with greater intensity and/or frequency, leading to a spike in media coverage, it often surprises investors, triggering price reactions. This may be due to limited investor attention, where the impact of climate change is only considered once it materializes. Alternatively, investors may rely too heavily on historical data, underestimating forward-looking projections, which delays the pricing of climate risks. Additionally, the inherent complexity and uncertainty of climate models may lead investors to discount these risks until they become more evident.

Overall, our paper highlights the complex interplay between physical climate risks and investor behaviors. The findings suggest that, generally, there is a positive risk premium associated with cyclone-related risks, while investors' perceptions of the severity of these risks could also significantly impact stock performance.

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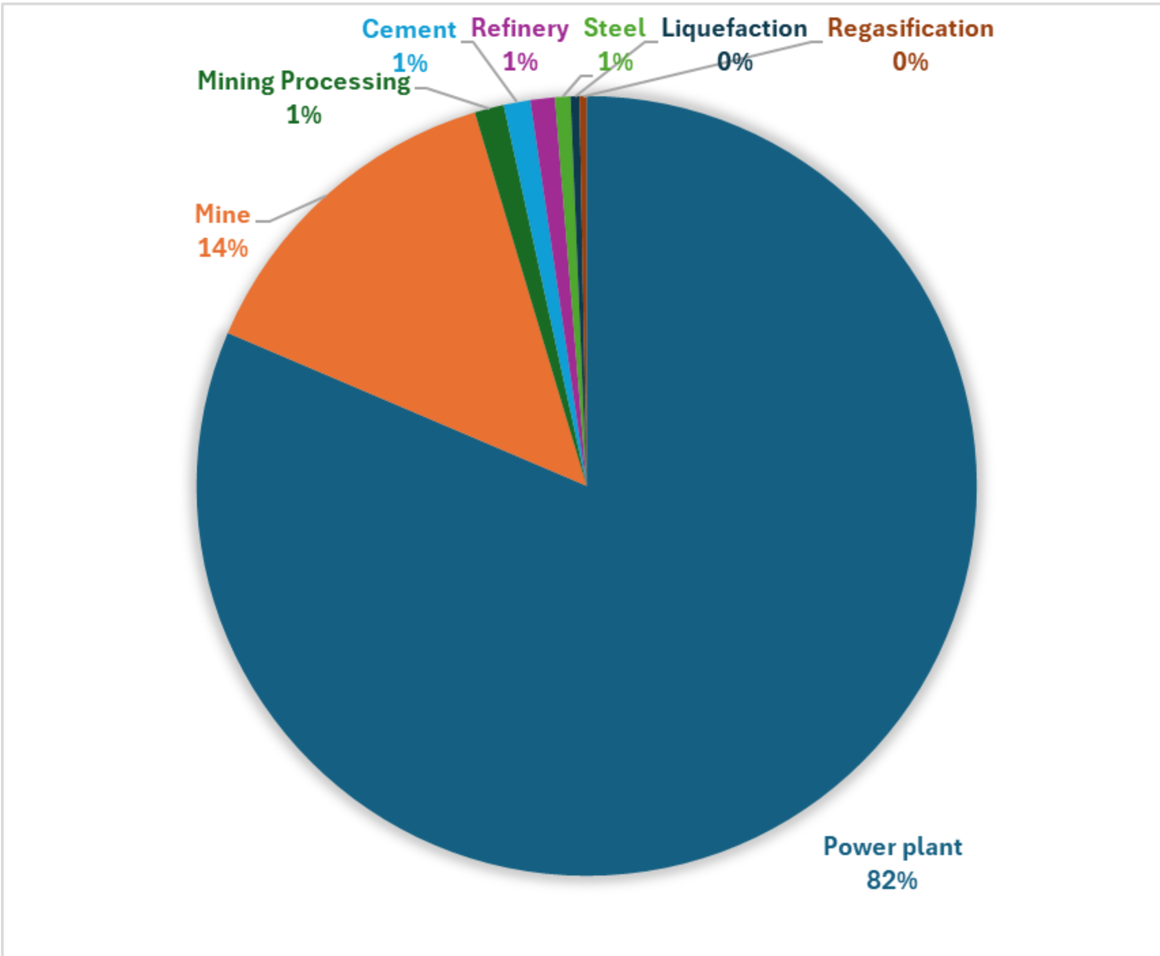
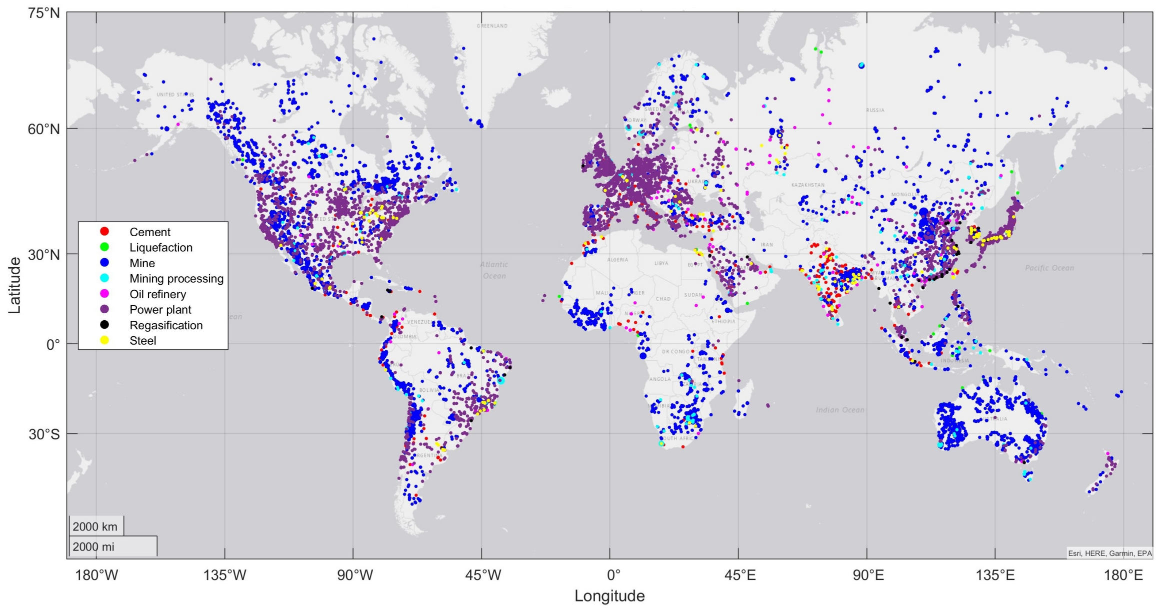
Figures and Tables

Figure 1: Distribution of Facilities by Type



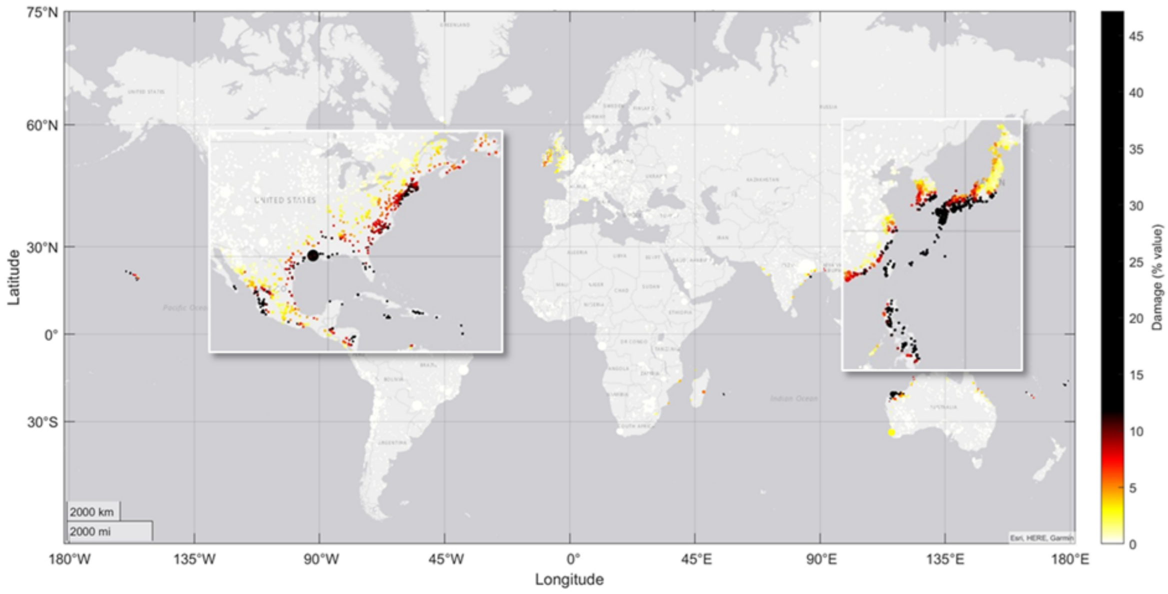
The pie chart illustrates the representativeness of each type of facility in the sample, with proportions calculated based on the number of facilities.

Figure 2: Geographic Distribution of Facilities



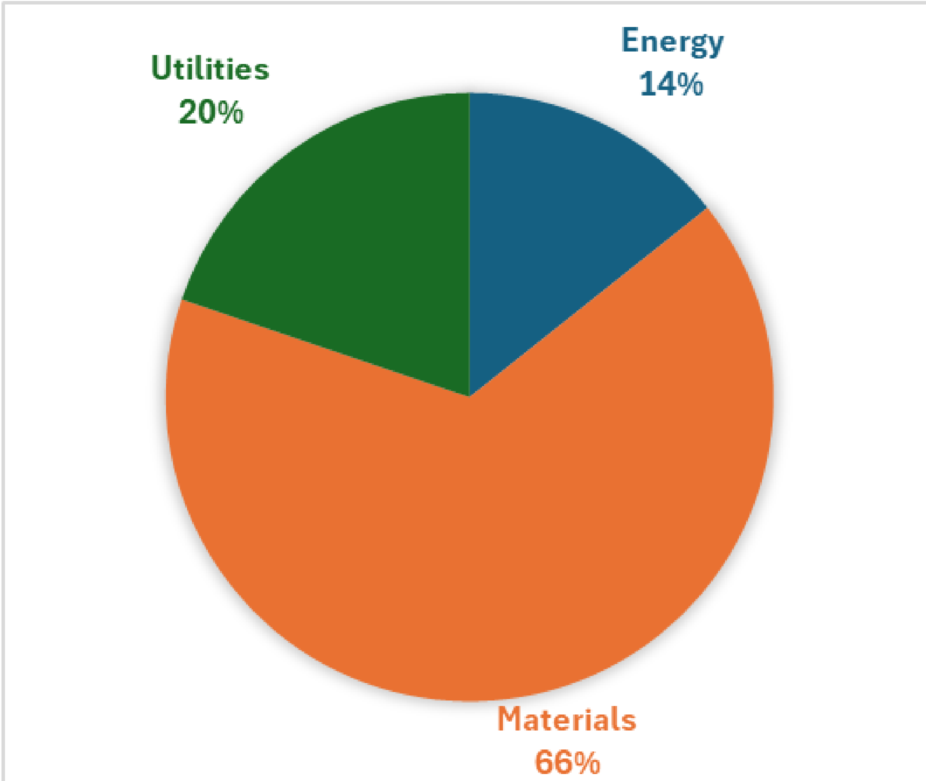
This plot illustrates the geographic distribution of facilities in our dataset. The colors represent different types of facility, including Cement, Liquefaction, Mines, Mining Processing, Oil Refineries, Power Plants, Regasification, and Steel facilities.

Figure 3: Exposure to Tropical Cyclone at the Facility-level



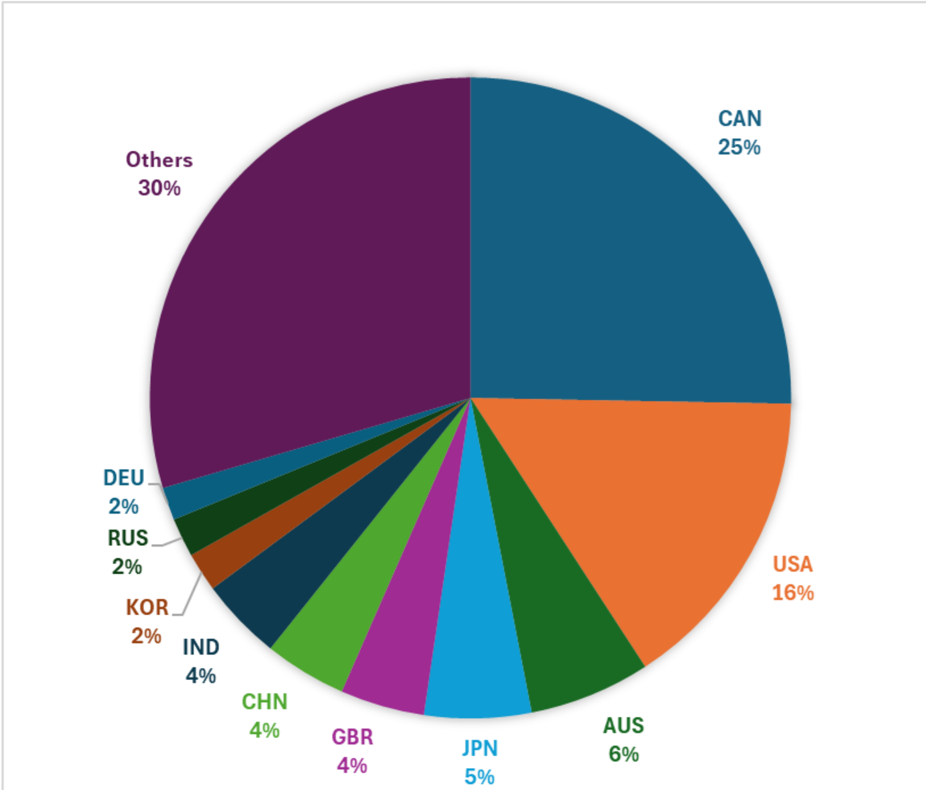
This plot highlights the exposure of facilities to tropical cyclones in the most vulnerable regions, including the Eastern Coast of the U.S., Central America, East and South East Asia. The exposure is measured by the damage caused by an RP100 event under the scenario RCP 4.5. The color and size of the circles represent the level of exposure and the facility's value, respectively.

Figure 4: Distribution of Firms by Sector



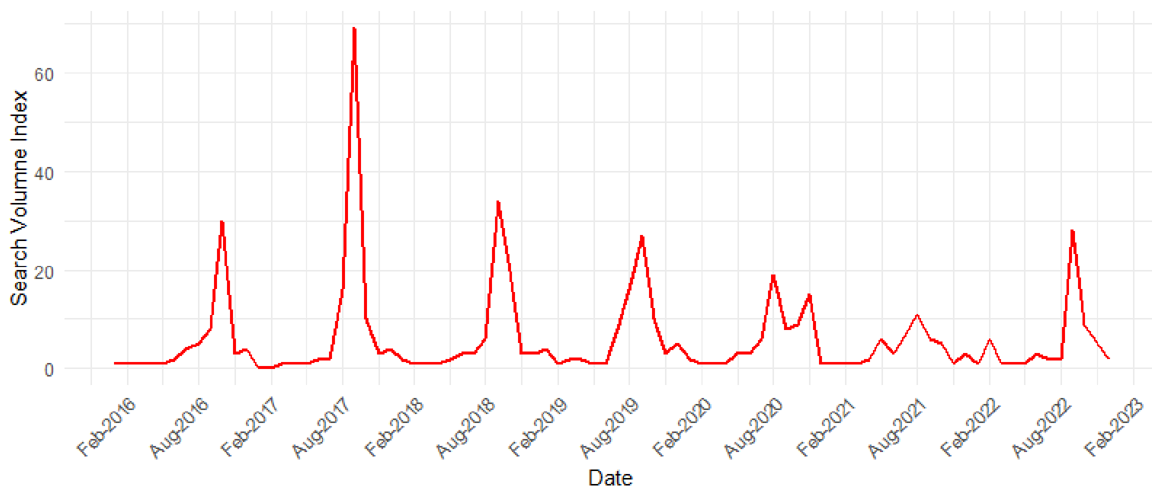
The pie chart illustrates the representativeness of each GICS two-digit sector in the sample, with proportions calculated based on the number of firms.

Figure 5: Distribution of Firms by Country of Incorporation



The pie chart illustrates the representativeness of each country of incorporation in the sample, with proportions calculated based on the number of firms.

Figure 6: Monthly Google Search Volume Index



The plot presents the time series of concerns about tropical cyclones at a monthly frequency using Google's SVI as a proxy for these concerns.

Table 1: Exposure to Tropical Cyclones by Sector and Country of Incorporation

Panel A: Risk Exposure by sector

		Expected Annual Impact (EAI)			Tail Impact (TI.RP50)		
GICS Sector	# of Firms	RCP2.6	RCP4.5	RCP6.0	RCP2.6	RCP4.5	RCP6.0
Energy	139	0.082	0.091	0.088	1.318	1.465	1.418
Materials	637	0.099	0.111	0.107	1.303	1.444	1.399
Utilities	191	0.129	0.143	0.139	1.632	1.804	1.749

Panel B: Exposure of Countries of Incorporation with the Highest Exposure

		Expected Annual Impact (EAI)			Tail Impact (TI.RP50)		
Country	# of Firms	RCP2.6	RCP4.5	RCP6.0	RCP2.6	RCP4.5	RCP6.0
Taiwan	11	1.91	2.11	2.04	14.89	16.14	15.74
the Philippines	7	0.95	1.05	1.01	11.89	12.79	12.50
Japan	52	0.59	0.66	0.64	6.30	6.89	6.71
Jamaica	1	0.58	0.63	0.62	12.71	13.60	13.31
South Korea	19	0.28	0.32	0.30	4.62	5.12	4.96
Cayman Islands	3	0.21	0.23	0.22	3.19	3.45	3.36
Luxembourg	2	0.18	0.28	0.25	3.62	4.68	4.34
UK	41	0.12	0.13	0.13	1.19	1.31	1.27
Colombia	4	0.10	0.12	0.11	2.37	2.58	2.52
France	13	0.10	0.11	0.11	2.07	2.18	2.14
Trinidad and Tobago	1	0.09	0.09	0.09	0.00	0.16	0.00
Australia	60	0.08	0.09	0.08	1.28	1.32	1.31
USA	150	0.08	0.09	0.08	1.76	1.99	1.92
Mexico	9	0.05	0.06	0.06	1.18	1.52	1.42
Ireland	3	0.04	0.04	0.04	0.77	0.78	0.78
India	40	0.04	0.04	0.04	0.73	0.76	0.75
Bangladesh	3	0.03	0.03	0.03	0.84	0.87	0.86
Chile	8	0.03	0.03	0.03	0.44	0.50	0.48
Canada	245	0.03	0.03	0.03	0.54	0.65	0.61
Bermuda	12	0.03	0.03	0.03	0.43	0.48	0.46
Singapore	1	0.02	0.02	0.02	0.03	0.03	0.03

The table shows the average expected annual impact (EAI) and Tail Impact (TI) for a 50-year return period (TI.RP50) for three sectors (Energy, Materials, and Utilities) in Panel A, and for the twenty countries with the highest average exposure in Panel B.

Table 2: Summary Statistics

Panel A: Risk Exposure Variables (as percentage of asset)

Statistic	N	Mean	St. Dev.	Min	Max
EAI (RCP2.6)	965	0.103	0.377	0.000	5.286
EAI (RCP4.5)	965	0.114	0.413	0.000	5.788
EAI (RCP6.0)	965	0.111	0.401	0.000	5.630
TI.RP50 (RCP2.6)	965	1.370	3.473	0.000	28.563
TI.RP50 (RCP4.5)	965	1.519	3.772	0.000	30.963
TI.RP50 (RCP6.0)	965	1.471	3.675	0.000	30.204
TI.RP100 (RCP2.6)	965	1.763	4.226	0.000	33.718
TI.RP100 (RCP4.5)	965	1.948	4.606	0.000	36.583
TI.RP100 (RCP6.0)	965	1.888	4.483	0.000	35.676
TI.RP250 (RCP2.6)	965	2.385	5.399	0.000	40.534
TI.RP250 (RCP4.5)	965	2.625	5.887	0.000	44.012
TI.RP250 (RCP6.0)	965	2.547	5.729	0.000	42.910
Panel B: Stock Returns and Control Variables					
RET (excess, monthly, in %, winsorized at 1%)	81,149	1.47	14.95	−32.50	60.19
SIZE (monthly, in log)	81,239	20.57	2.33	10.83	26.86
B/M (monthly, winsorized at 2.5%)	81,239	1.00	0.92	0.07	4.83
LEVERAGE (quarterly, winsorized at 2.5%)	81,239	0.17	0.16	0.00	0.57
INVEST/A (quarterly, winsorized at 2.5%)	81,239	0.04	0.04	0.00	0.20
ROE (quarterly, winsorized at 2.5%, in %)	81,239	−0.97	9.88	−44.04	18.56
PPE (quarterly, in log)	81,239	6.37	2.87	−7.22	12.47
MOM (monthly, in %)	81,239	1.81	5.12	−10.82	27.42
VOL (monthly, in %)	81,239	13.82	9.63	2.42	69.63

This table reports the summary statistics for the variables used in the regressions. The sample period is 2016-2022 (for accounting and market data). Panel A reports the physical risk variables as a percentage of total physical assets. EAI is the expected annual impact from all events. TI.RP50 is the expected impact from events that corresponds to a return period of 50 years. Panel B reports the cross-sectional variables. RET is monthly return; LOGSIZE is the natural logarithm of market capitalization (in dollars), B/M is the book value of equity divided by the market capitalization; LEVERAGE is the book value of long-term debt divided by the book value of total assets; INVEST is the capital expenditure divided by the book value of total assets; ROE is the net income divided by book value of equity; LOGPPE is the natural logarithm of plants, property and equipment; MOM and VOL are the average and standard deviation of the last twelve-month returns (month t included).

Table 3: Correlations between Different Measures for Exposure to Tropical Cyclones

EAI (RCP2.6)	EAI (RCP4.5)	EAI (RCP6.0)	TI.RP50 (RCP2.6)	TI.RP50 (RCP4.5)	TI.RP50 (RCP6.0)	TI.RP100 (RCP2.6)	TI.RP100 (RCP4.5)	TI.RP100 (RCP6.0)	TI.RP250 (RCP2.6)	TI.RP250 (RCP4.5)	TI.RP250 (RCP6.0)
1.000	0.999	1.000	0.904	0.899	0.901	0.867	0.860	0.863	0.824	0.818	0.820
0.999	1.000	1.000	0.906	0.903	0.905	0.871	0.866	0.868	0.829	0.825	0.826
1.000	1.000	1.000	0.906	0.902	0.904	0.870	0.864	0.866	0.827	0.823	0.824
0.904	0.906	0.906	1.000	0.997	0.998	0.990	0.984	0.986	0.965	0.959	0.961
0.899	0.903	0.902	0.997	1.000	1.000	0.993	0.991	0.992	0.973	0.970	0.971
0.901	0.905	0.904	0.998	1.000	1.000	0.993	0.990	0.991	0.971	0.968	0.969
0.867	0.871	0.870	0.990	0.993	0.993	1.000	0.998	0.999	0.992	0.988	0.990
0.860	0.866	0.864	0.984	0.991	0.990	0.998	1.000	1.000	0.993	0.993	0.993
0.863	0.868	0.866	0.986	0.992	0.991	0.999	1.000	1.000	0.993	0.992	0.993
0.824	0.829	0.827	0.965	0.973	0.971	0.992	0.993	0.993	1.000	0.999	0.999
0.818	0.825	0.823	0.959	0.970	0.968	0.988	0.993	0.992	0.999	1.000	1.000
0.820	0.826	0.824	0.961	0.971	0.969	0.990	0.993	0.993	0.999	1.000	1.000

Table 4: Exposure to Tropical Cyclones and Stock Returns - Expected Annual Impact (EAI)

	RCP 2.6	RCP 4.5	RCP 6.0	RCP 2.6	RCP 4.5	RCP 6.0
EAI	-0.09	-0.08	-0.08	-0.05	-0.04	-0.04
	(0.06)	(0.06)	(0.06)	(0.08)	(0.07)	(0.07)
Observations	81,149	81,149	81,149	81,149	81,149	81,149
R^2	0.26	0.26	0.26	0.26	0.26	0.26
Industry FE	N	N	N	Y	Y	Y
MonthYear FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y

This table presents the cross-sectional regressions of monthly excess stock return on firms' exposure to tropical cyclones measured by the expected annual impact (EAI) and other controls. Month-year and country of incorporation fixed effects are included in all regressions. GICS industry fixed effects are included in columns 4 - 6. Standards errors in the parentheses are clustered by firm. Control variables include LOGSIZE, B/M, LEVERAGE, INVEST/A, ROE, LOGPPE, MOM and VOL. See table 2 for the definitions of variables. The sample period is 2016-2022 (for accounting and market data).

Table 5: Exposure to Tropical Cyclones and Stock Returns - Tail Impact (TI)

	RP 50 years			RP 100 years			RP 250 years		
	RCP 2.6	RCP 4.5	RCP 6.0	RCP 2.6	RCP 4.5	RCP 6.0	RCP 2.6	RCP 4.5	RCP 6.0
TI	-0.01	-0.01	-0.01	-0.004	-0.003	-0.004	-0.002	-0.001	-0.001
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	81,149	81,149	81,149	81,149	81,149	81,149	81,149	81,149	81,149
R^2	0.26	0.26	0.26	0.26	0.26	0.26	0.26	0.26	0.26
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
MonthYear FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

This table presents the cross-sectional regressions of monthly excess stock return on firms' exposure to tropical cyclones measured by the tail impact (TI) and other controls. Month-year and country of incorporation are included in all regressions. GICS industry fixed effects are included in columns 4 - 6. Standards errors in the parentheses are clustered by firm. Control variables include LOGSIZE, B/M, LEVERAGE, INVEST/A, ROE, LOGPPE, MOM and VOL. See table 2 for the definitions of variables. The sample period is 2016-2022 (for accounting and market data).

Table 6: Risk Exposure and Stock Returns, Interaction with Concerns about Tropical Cyclones

	RCP 2.6	RCP 4.5	RCP 6.0	RCP 2.6	RCP 4.5	RCP 6.0
EAI	0.42**	0.39**	0.40**	0.23**	0.21**	0.22**
	(0.20)	(0.18)	(0.19)	(0.11)	(0.10)	(0.10)
$EAI \times SVI$	$-$0.31***	$-$0.29***	$-$0.29***			
	(0.12)	(0.11)	(0.11)			
$EAI \times HIGH.SVI$				$-$0.74***	$-$0.68***	$-$0.70***
				(0.20)	(0.18)	(0.19)
Observations	80,316	80,316	80,316	80,316	80,316	80,316
R^2	0.26	0.26	0.26	0.26	0.26	0.26
MonthYear FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y

This table presents the cross-sectional regressions of monthly excess stock return on firms' exposure to tropical cyclones (measured by EAI), and the interaction with the Google Search Volume Index (SVI) in column 1-3, and the interaction with an indicator for high SVI ($HIGH.SVI$) in column 4-6. $HIGH.SVI$ takes the value of 1 if the Google SVI in the current month is larger than the median in the sample period and 0 otherwise. Controls, their interactions, month-year, country, and industry fixed effects are included in all regressions. Standard errors in parentheses are clustered by firm. Control variables include LOGSIZE, B/M, LEVERAGE, INVEST/A, ROE, LOGPPE, MOM, and VOL. See table 2 for definitions of variables. The sample period is 2016-2022.

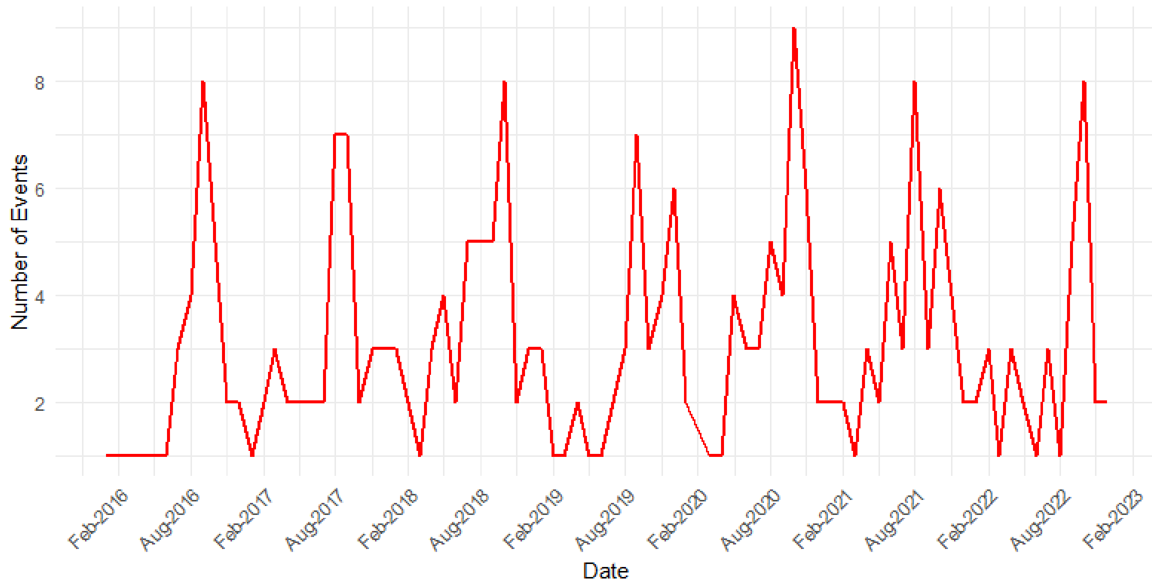
Table 7: Risk Exposure and Stock Returns, Interaction with Shocks to Concerns

	RCP 2.6	RCP 4.5	RCP 6.0
EAI	0.14	0.13	0.14
	(0.23)	(0.21)	(0.22)
$EAI \times SVI.SHOCK$	-0.62^{***}	-0.57^{***}	-0.58^{***}
	(0.19)	(0.18)	(0.18)
$EAI \times SVI.EXP$	-0.17	-0.16	-0.16
	(0.14)	(0.12)	(0.13)
Observations	80,316	80,316	80,316
R^2	0.26	0.26	0.26
MonthYear FE	Y	Y	Y
Country FE	Y	Y	Y
Industry FE	Y	Y	Y

This table presents the cross-sectional regressions of monthly excess stock return on firms' exposure to tropical cyclones (measured by EAI), with interactions with the expected and unexpected components of concerns about cyclones using Google SVI. The shock component $SVI.SHOCK$ is the difference between realizations and the expected Google SVI $SVI.EXP$. The expected component equals the month-m historical mean computed using historical data from January 2008 (when Google news search volume index is available) to the same month in the previous year. Controls, their interaction with $SVI.SHOCK$ and $SVI.EXP$, month-year, country of incorporation, and industry fixed effects are included in all regressions. Standard errors in parentheses are clustered by firm. Control variables include LOGSIZE, B/M, LEVERAGE, INVEST/A, ROE, LOGPPE, MOM, and VOL. See table 2 for definitions of variables. The sample period is 2016-2022 (for accounting and market data).

APPENDIX

Figure A1: Monthly Counts of Cyclone Events



The plot presents the time series of concerns about tropical cyclones at a monthly frequency using the counts of tropical cyclone events from the EM-DAT (Emergency Events Database).

Table A1: Risk Exposure and Stock Returns, Interaction with Concerns about Tropical Cyclones

	RCP 2.6	RCP 4.5	RCP 6.0	RCP 2.6	RCP 4.5	RCP 6.0
EAI	0.64***	0.59***	0.61***	0.17*	0.16*	0.16*
	(0.16)	(0.15)	(0.15)	(0.10)	(0.09)	(0.09)
$EAI \times NO.EVENTS$	−0.22***	−0.20***	−0.21***			
	(0.05)	(0.04)	(0.05)			
$EAI \times HIGH.NO.EVENTS$				−0.78***	−0.71***	−0.73***
				(0.25)	(0.23)	(0.23)
Observations	78,293	78,293	78,293	78,293	78,293	78,293
R^2	0.26	0.26	0.26	0.26	0.26	0.26
MonthYear FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y

This table presents the cross-sectional regressions of monthly excess stock return on firms' exposure to tropical cyclones (measured by EAI) and the interaction with the monthly number of cyclone events ($NO.EVENTS$) in column 1 -3, and with an indicator for high monthly number of cyclone events ($HIGH.NO.EVENTS$) in column 4-6. $HIGH.NO.EVENTS$ takes the value of 1 if the number of events in the current month is greater than the median in the sample period and 0 otherwise. Controls, their interactions with $NO.EVENTS$ or $HIGH.NO.EVENTS$, and fixed effects for month-year, country, and industry are included in all regressions. Standard errors in parentheses are clustered by firm. Control variables include LOGSIZE, B/M, LEVERAGE, INVEST/A, ROE, LOGPPE, MOM, and VOL. The sample period is 2016-2022 (for accounting and market data).

Table A2: Risk Exposure and Stock Returns, Interaction with Shocks to Concerns

	RCP 2.6	RCP 4.5	RCP 6.0
EAI	0.36	0.33	0.34
	(0.25)	(0.23)	(0.22)
$EAI \times NO.EVENTS.SHOCK$	-0.26^{***}	-0.24^{***}	-0.25^{***}
	(0.05)	(0.05)	(0.05)
$EAI \times NO.EVENTS.EXP$	-0.12	-0.11	-0.11
	(0.08)	(0.07)	(0.08)
Observations	78,293	78,293	78,293
R^2	0.26	0.26	0.26
MonthYear FE	Y	Y	Y
Country FE	Y	Y	Y
Industry FE	Y	Y	Y

This table presents the cross-sectional regressions of monthly excess stock return on firms' exposure to tropical cyclones (measured by EAI), its interaction with the expected and unexpected components of concerns about cyclones (proxied by the number of cyclone events). The shock component $NO.EVENTS.SHOCK$ is the differences between the realizations and the expected number of cyclones $NO.EVENTS.EXP$. The expected component equal the month-m historical mean computed using historical data from January 2000 to the same month in the previous year. Controls, their interaction with $NO.EVENTS.SHOCK$, $NO.EVENTS.EXP$, month-year, country of incorporation, industry fixed effects are also included in all regressions. Standards errors in the parentheses are clustered by firm. Control variables include LOGSIZE, B/M, LEVERAGE, INVEST/A, ROE, LOGPPE, MOM and VOL. See table 2 for the definitions of variables. The sample period is 2016-2022 (for accounting and market data).

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