Does the stock market price physical climate risks?

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Abstract

This paper develops a bottom-up, forward-looking measure of hurricane risk exposure based on a probabilistic assessment of damages to companies' physical assets and assesses whether this physical climate risk is priced by global equity markets. Average expected losses on physical assets due to hurricane and expected losses that would occur for rare hurricane events are estimated in three different climate scenarios (RCP 2.6, 4.5 and 6.0). Our results show that a one standard deviation higher cyclone exposure is associated with a 2.2% higher annual return during "quiet" years, while it is associated with a -0.7% annual return during years of intense (above median) cyclone activity. Firms with high hurricane exposure, lower profitability and lower investment are particularly affected. Overall, the market appears to price physical risks related to tropical cyclones. But the premium fades out during years of high cyclone activity.

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1 Introduction

Climate change, and the natural disasters associated with it, will have large negative socio-economic impacts (IPCC 2022), negatively affecting corporate profits (Gianfrate et al. 2021), and leaving some firms particularly vulnerable (Bressan et al. 2022). In this regard, Fan and Bevere (2020) estimate that weather-related events such as storms, floods, droughts, and wildfires caused global annual economic losses of USD 212 billion (bn) on average over the last decade, and climate disasters might be even more severe in the future.

With growing climate change, risks of extreme weather events are becoming much less diversifiable (Golub et al. 2022). In addition, insurance products against climate-related events are either not existing in most countries, or very expensive, thus leaving firms and houses to an insurance protection gap (ECB/EIOPA 2022[1]). The standard asset-pricing theory posits that investors should be compensated for holding stocks that are exposed to bad states of nature (i.e., the occurrence of natural disasters). However, there is mixed empirical evidence on the extent the market can incorporate physical risk into prices across asset classes and type of hazards (see e.g. Nguyen et al. 2022, Garbarino and Guin 2021, Bressan et al. 2022, Acharya et al. 2023, Gostlow (2021)). This is due to several reasons. First, future climate-related losses are complex to estimate, considering the uncertainty associated to scenarios of future realizations (Hain et al. (2022)). Meanwhile, market participants may have little experience in identifying and quantifying such risks (UNEP FI 2017). Second, financial decisions are often affected by behavioral biases, bounded rationality, or heterogeneity in beliefs (Battiston et al. 2021, Dunz et al. 2021), which can result in the mispricing of some type of risks. Therefore, a better understanding of the extent to which markets are pricing climate risks - and what kind of risks (transition, physical, acute vs chronic, etc.) should be of interest of investors and supervisors. In particular, it is crucial to understand how much investors are compensated for bearing climate physical risks, and what are the losses suffered when climate disasters materialize.

One important challenge of asset pricing tests is the lack of reliable estimates of firms' exposure to climate physical risk. Recent studies have built measures for climate change-related risks based on textual data such as firms' own disclosure (Nagar and Schoenfeld (2022)), earnings calls (Sautner et al. (2023)), or from general climate change-related news (Faccini et al. (2022); Engle et al. (2020)). Text-based exposures can be noisy measures for several reasons. First, disclosure tends to focus on the Greenhouse Gas emissions dimension, which tells us little about the exposure to physical risk (TCFD 2017[2]). Additionally, firm's communication on risk exposure can be handled strategically and might not fully reflect the risks or damages a firm is facing. In practice, firms' disclosure of climate change-related risk is still limited, non-compulsory in many countries, and may largely depend on management's

[1] https://www.eiopa.europa.eu/publications/annual-report-2022_en#details
[2] https://www.fsb-tcfd.org/publications/final-recommendations-report/

choice of expressions. Media coverage typically concentrates at times when a natural disaster hits a given firm and reflects more actual losses than risk exposures. Moreover, in certain periods, concerns about climate change can be crowded out by concurrent concerns such as COVID-19 (Sautner et al. (2023)). Other studies rely on historical climate data (Hong et al. (2019)) or commercial climate risk scores (Gostlow (2021)), typically built on three components: hazard specific to locations, exposure of firms, and vulnerability at the facility level. While the first component is fairly transparent due to the public availability of climate models, the second and third are more difficult to assess and highly dependent on proprietary data. This can lead to a substantial divergence of commercial risk scores as documented in Hain et al. (2022).

In this paper, we propose forward-looking measures of risk based on probabilistic assessment of damages to companies' physical assets, as computed by the CLIMADA model (Aznar-Siguan and Bresch (2019)). In particular, we estimate the average expected losses on physical assets due to hurricane (expected annual impact) and the expected losses that would occur for rare hurricane events (tail impact) in three different climate scenarios (RCP 2.6, 4.5 and 6.0). We then assess whether physical climate risk related to tropical cyclones is priced by the equity market. Cyclones-related risks have been shown to be the most destructive natural disasters worldwide in terms of dollar losses, and the number of such events has doubled since 1980 (Hoeppe (2016)). A clear advantage of our methodology with respect to commercially available physical risk scores (e.g. Moody's 427 scores) is the fact that our measure is transparent and replicable. It also allows to flexibly adjust the climate scenarios considered for the estimation.

Our results are as follows. At first sight, and whatever the measure of firms' exposure we consider (expected annual impact or tail impact), cyclone risk does not seem to be priced by the market, thus confirming the results by Braun et al. (2021), Faccini et al. (2022) or Sautner et al. (2022). However, historical stock returns are likely to be affected by cyclone activity happening during our sample period. During a "busy" cyclone season, firms having high exposure to cyclones are likely to be affected more negatively compared to those having low exposure, as the realization of cyclones (the losses or expected losses associated to it) may affect them negatively. We thus interact our cyclone exposure variable with a measure of overall cyclone activity. We find that a one standard deviation higher cyclone exposure is associated with a 2.2% higher annual return during "quiet" years, while it is associated with a -0.7% annual return during years of intense (above median) cyclone activity. Firms with high hurricane exposure, with lower profitability and lower investment are particularly affected. Overall, the market appears to price physical risks related to tropical cyclones. But the premium fades out during years of high cyclone activity.

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 Literature Review

Our paper contributes to the growing literature that studies whether climate physical risks are priced on the equity market. Recent studies rely on textual analysis of news, companies' annual reports or call transcripts to build measures of climate risk exposure. Faccini et al. (2022) build climate change-related risk factors using textual and narrative analysis of Reuters climate change news. In particular, they classify climate risk factors into several categories including natural disasters and global warming. The paper, however, finds no significant risk premium for physical risks exposures. Nagar and Schoenfeld (2022) construct a climate change risk measure using firms' disclosure of weather risk in their annual reports 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. (2022) build a firm-specific climate change exposure measure from corporate call transcripts, capturing the attention devoted to a large variety of climate shocks (decomposed into opportunities, regulatory and physical shocks). They show that there is 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 rely on historical weather data or model-based climate risk scores to extract physical risk premiums. One of the early studies on the pricing of physical risk, Hong et al. (2019), uses 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) uses 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 returns of 6.5% per year over the period 1995-2019. However, this risk premium is only significant among firms that operate domestically (thus not globally diversified) and among 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. This is confirmed by Deghi et al.

(2021) who 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, but also 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 considers firms' exposure to sea-level rise, hurricanes, heat stress, and extreme rainfalls. In this paper, instead of using the conventional two-pass procedure to estimate the risk premia as described above, the author uses the three-pass procedure introduced in Giglio and Xiu (2021) to control for omitted factors and remove measurement errors. The paper 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). However, the proportion of physical risk factors that is priced is only from 8% to 38% and the unpriced portions of physical climate risks co-vary with latent factors (and can be explained by industry returns, common risk factors, and realisations of severe weather events), suggesting that financial markets struggle to price the risk.

In our paper, we also use science-based methodologies to map projected damage due to cyclones of assets in various locations to firms' revenue. However, rather than relying on commercial dataset for physical risk exposure, we build a physical risk metric. Our paper is thus also closely connected to papers providing climate physical risk assessment. In particular, we rely on Bressan et al. (2022), who develop a methodology to quantify hurricane risks on geolocalized productive assets, considering their exposure to both chronic and acute impacts across IPCC scenarios. Applying the methodology to a sample of listed firms with activities located in Mexico, they find that investor losses are underestimated up to 70% when neglecting asset-level information, and up to 82% when neglecting acute risks. In this paper, we rely on a similar method to estimate physical risk exposure at the firm level.

3 Data and Methodology

3.1 Firm-level physical risk estimates

Our sample consists of all companies that we can identify as owners of physical assets (i.e. productive facilities). We collect information about 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. (2022)). The choice of asset types that we consider is conditioned by data availability. The total number of physical assets in our data set is 24,668 globally. We then reconstruct ownership chains for each asset. Ownership chains could be reconstructed for 1,606 companies and 18,638 assets. The assets' distribution is represented in Figure 1, from which we can see that the most represented assets are power plant units (with 11,844 assets), followed by mines (5,403 assets).

For 1,606 companies we construct a measure of physical climate risk, by focusing on hazards from tropical cyclones. Our measure of physical risk of companies is based on the probabilistic climate acute risk assessment of damages caused by hurricanes, 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 at year 2050 for three Representative Concentration Pathways (RCP) scenarios (2.6, 4.5, 6.0). First, we retrieve 5,970 tracks of tropical cyclones that occurred in all the tropical cyclone basins between 1950 and 2021 from the International Best Track Archive for Climate Stewardship (IBTrACS)[3]. For each historical event, we simulate additional 30 synthetic tracks, needed for the probabilistic assessment with a random track generator and using the Holland (2008) wind field model. After removing the duplicated tropical cyclones' tracks, we are left with 138,849 (real and simulated) cyclones. We map tracks to a global grid of centroids[4], and using the CLIMADA sofware (Aznar-Siguan et al. (2022)), we perturb the tracks of tropical cyclones to account for changes in tropical cyclones' intensities and frequencies caused by climate change impacts. CLIMADA uses the results obtained by Knutson et al. (2015), and applies linear interpolation for various RCP scenarios. We consider the expected impact for year 2050. For each asset in our database, we identify the closest centroid on the global grid of centroids, and compute the wind speed in a given scenario. Then, using the damage function from Emanuel (2011), we estimate the damages from wind to each asset. In the functional specification in Emanuel (2011), damages vary as the cube of wind speed that exceeds an estimated threshold; percentage change of damaged property approaches unity at very high wind speeds, but never exceeds unity [5].

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

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}), by considering $W_{threshold}$ (i.e. the wind speed below which no damages occur) and W_{half} (i.e.

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

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

[5] Damage function in Equation 1 takes into account 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)). Furthermore, although companies have different adaptation strategies, the company-level data about adaptation efforts is not easily accessible, so we do not account for adaptation measures in the damage function.

the wind speed at which half of the property value is destroyed). Following Bressan et al. (2022), we use the same damage function across all asset types because the lack of available data does not allow us to calibrate the damage function for each specific type of asset in each geographic region. For each physical asset and each event (both historical and synthetic), we compute the fraction of the asset's value that gets 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[6].

To obtain our physical risk metric, we first compute expected annual impact (EAI) for each physical asset j, in each RCP scenario s, at 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 hurricane 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.)[7]. 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.

Our measure of company's exposure to tail risk is the loss that is exceeded at a fixed low annual frequency (1/50, 1/100, 1/250), or damage from tropical cyclones with a certain return period (i.e. RP50, RP100, and RP250) or higher, 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. The variable TI reported in table 1 and 2 is the product of the value of loss (corresponding to a certain return period and a RCP scenario) and its corresponding annual probability of occurrence:

$$TI_{jsr} = x_{jsr} p_r, \tag{4}$$

[6]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 5); if the value of an asset increased/decreased over time, damages would increase/decrease accordingly, but the relative damages would remain the same.

[7]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`

where TI_{jsr} is the tail impact for asset j, in scenario s and return period r, x_{jsr} is the loss corresponding to the return period r, p_r is the annual probability of occurrence. We provide details for the computation of the annual probability of occurrence in the appendix. Similar to EAI, the measure for tail impact is also a measure in expectation. Accordingly, an exposure that equals 0.01% for RP50 means that, in expectation, in 2050, such a firm has 0.01% of its physical assets destroyed by the type of cyclones of a strength similar to the one of the cyclones that, on average, occur every fifty years or less frequently.

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. We therefore restrict our sample to firms operating in the Energy, Materials, and Utilities sectors. Hain et al. (2022) also shows that companies in these three sectors are indeed the most exposed to physical risks. Figure 2 shows the sector-level distribution of firms in the sample. The final sample (after matching with financial data) includes 789 firms, out of which, 71% (563 firms) are in the Materials sector, 16% (124 firms) are in the Utilities sector and 13% (102 firms) are in the Energy sector. In terms of physical risk exposure, 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 of 0.15%[8] (TI of 0.02 %), followed by Materials and Energy at 0.12% and 0.08% (TI of 0.01%) in scenario RCP 4.5. There is also a significant variation within each sector. For example, in the Materials sector, the firm at the 20th percentile has an EAI of 0% while the one at the 80th percentile has an EAI of 0.5%.

Figure 3 shows the distribution of firms by country of incorporation. The largest country by number of firms in the sample is Canada with 222 firms (28%), followed by the United States with 88 firms (11%). Panel B of Table 1 presents ten countries that are most exposed to tropical cyclones and ten that are least exposed. Countries with the highest exposure include Taiwan, the Philippines, and Japan with average EAI of 1.91%, 0.95%, and 0.67% (in scenario RCP 4.5). This also holds true for the TI measures. On the other spectrum, thanks to their geographical locations, many countries have almost no exposure to tropical cyclone risks regardless of the measures and scenarios.

Panel A of Table 2 shows the summary statistics of the exposure to cyclones. In the climate scenario RCP 4.5, the average firm in the sample has an EAI of 0.089% and a TI of roughly 0.012%, 0.010%, and 0.010% for the three return periods of 50, 100, and 250 years. Notice the damage in dollars of rare events should be the largest for an event of the 250-year return period, followed by the return period 100, and finally 50. However, the probability of occurrence of such events is in the opposite order. Consequently, the expected damage (TI) is similar for the three return periods. On the one hand, as shown in table 5, the correlations between EAI and TI in different RCP scenarios are all above 0.80, suggesting that exposure

[8] This means an average expected loss of 0.15% of firms' physical assets in 2050

to cyclones is mainly driven by the locations of facilities. On the other hand, we still observe higher EAI and TI for the scenario RCP 4.5 and RCP 6.0 compared to RCP 2.6.

3.2 Financial data

Financial data from Compustat North America and Compustat Global for the period 2016-2022 is merged with the sample of firms for which physical damage data is available using the ISIN/GVKEY identifier. The ultimate matching produces 68,806 firm-month observations on 789 unique firms incorporated in sixty-two countries.

The dependent variable in our cross-sectional analysis $RET_{i,t}$ is the monthly excess return of stock i for month t. We obtain price data from Compustat North America and Compustat Global. The total returns are computed from the adjusted closing prices and total return factor to take into account cash distribution and reinvestment 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 obtain accounting data at a quarterly frequency from Compustat. For firms whose reporting currencies are not US dollars, we first convert their accounting figures into US dollars using the monthly exchange rate provided by Compustat. 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. When quarterly net income is not available, such as in the case of firms incorporated in Japan, we use end-of-year net income divided by four as quarterly income. $LOGPPE_{i,t}$ 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).

We report the summary statistics of these variables in Panel B of Table 2. The average monthly stock return in excess of the risk-free rate is 1.55%, with a standard deviation of 16.05%. An average firm in our sample has a market capitalization of $175.6 million. The average book-to-market ratio and the average leverage are 1.06 and 0.16 respectively.

4 Results

4.1 Exposure to cyclones and stock returns

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

$$RET_{i,t} = \alpha_0 + \alpha_1 EXPOSURE_i + \alpha_2 Controls_{i,t} + \delta_{industry} + \delta_{country} + \delta_t + \epsilon_{i,t} \quad (5)$$

The dependent variable $RET_{i,t}$ is the monthly stock return for firm i in month-year t. In the main results, the independent variable $Exposure_i$ is EAI in each of the three representative concentration pathways RCP 2.6, RCP 4.5, and RCP 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 are associated with stock returns, including the natural logarithm of firms' market capitalization ($LOGSIZE$), book-to-market ratio (B/M), book leverage ($LEVERAGE$), the ratio of end-of-year capital expenditure over book value of assets ($INVEST/A$), return on book value of equity (ROE), the logarithm of firms' property, plant & equipment ($LOGPPE$), last twelve-month average returns and volatility (MOM and VOL). We control for country of incorporation fixed effect and month-year fixed effect ($\delta_{country}$ and δ_t, respectively). Since exposure to physical risks is partly determined by how vulnerable the facilities are to cyclones, a feature that is industry-specific, we therefore control for industry fixed effect ($\delta_{industry}$) in the main specifications. To check the robustness of our results, we also test our main regressions without these industry fixed effects, with similar results. Standard errors are clustered at the firm level.

Table 4 reports the coefficients on EAI for the full sample period from January 2016 to December 2022. Columns 1 - 3 show the results without industry fixed effect, and columns 4 - 6 with industry fixed effect. The reported coefficients are small in magnitude and insignificant in all columns, suggesting that exposures to tropical cyclones are generally not priced by the market. This is robust across and within industry. The magnitudes of impact are also very similar in different RCP scenarios. We repeat the above analysis using TI as a measure for exposures to tail risks and report the result in Table 5. For all scenarios and return periods, there are positive, yet again insignificant premium associated with the exposure to tail risks.

Combining the analysis in Table 4 and Table 5, one may want to conclude that the market does not price climate risks related to cyclones. However, we interpret this result with an important caveat. Historical returns which we use as a proxy for expected returns are likely to be affected by the realization of cyclones during the sample period. Although on average, one may expect a positive risk premium for firms with high exposure to cyclones, a realization of this risk may lead to a significant loss in firms' physical assets, resulting in negative stock returns instead. Consequently, the estimated coefficients in (5) may appear negative or zero. In the subsection that follows, we look at the impact of exposure on stock returns, conditional on cyclone activity.

4.2 Time-varying tropical cyclone activity

Historical stock returns are likely to be affected by cyclone activity near the locations of firms' facilities. During a "busy" cyclone season, firms having high exposure to cyclones are likely to be affected more negatively compared to those having low exposure. On the contrary, during a "quiet" cyclone season, one may expect these high-exposure firms to earn higher returns (a risk premium) relative to the low-exposure ones. To test this hypothesis, we estimate the following models:

$$\begin{aligned} RET_{i,t} &= \alpha_0 + \alpha_1 EXPOSURE_i + \alpha_2 EXPOSURE_i \times CYC.ACTV \\ &+\alpha_3 Controls_{i,t} \times CYC.ACTV + \delta_{industry} + \delta_{country} + \delta_t + \epsilon_{i,t} \end{aligned} \tag{6}$$

where $CYC.ACTV$ is the annual total number of cyclones that occurred in the Atlantic and Pacific basins. The data is obtained from the Tropical Cyclone Reports (TCR)[9]. All other variables remain the same as in equation 5. We expect α_1 to be positive - firms with higher exposure to cyclones should earn higher returns on average; α_2 to be negative - firms with higher exposure should suffer more when cyclones occur. The sum $\alpha_1 + \alpha_2 \times CYC.ACTV$ that varies by year reflects how the impact of exposure on stock returns changes as a function of cyclone activity.

Panel A of Table 6 shows the coefficients α_1 and α_2 estimated from the model 6. We do not include industry fixed effects in columns 1 - 3 and do so in columns 4 - 6. The results show that in all scenarios, across and within industry, the coefficient α_1 is positive and significant, implying a higher return for highly-exposed firms at least when $CYC.ACTV$ is low. At the same time, the negative and significant loading on the interaction term α_2 suggests that the positive impact of exposure on returns would deteriorate as $CYC.ACTV$ gets higher. The impact $\alpha_1 + \alpha_2 \times CYC.ACTV$ varies year by year depending on cyclone activity. In "quiet" years such as 2022 (with only 35 cyclones), the coefficient on EAI from column 4 is 0.51 ($4.36 - 0.11 \times 35$). This impact is economically significant. One standard deviation increase in exposure to cyclones is compensated with 0.17 percentage points higher (0.51×0.34) monthly stock return (2.1 percentage points higher annualized returns). Conversely, in "busy" years such as 2020 (with 51 cyclones), the coefficient on EAI is -1.25 ($4.36 - 0.11 \times 51$). A one standard deviation increase in exposure to cyclones is associated with a drop of -0.43 percentage points in monthly return (5.7 percentage points in annualized return).

[9] `https://www.nhc.noaa.gov/data/tcr/index.php`

To ease the interpretation, in Panel B of the Table 6, we replace $CYC.ACTV$ by an indicator $HIGH.ACTV$ that takes the value of 1 when $CYC.ACTV$ is higher or equal to the median and 0 otherwise. From column 4, one standard deviation higher exposure is associated with 0.18 percentage points (0.53×0.34) higher monthly return during "quiet" years while it is associated with a drop of 0.05 percentage points ($(0.53 - 0.69) \times 0.34$) in monthly return during "busy" years (respectively 2.2 and -0.7 percentage points in annual returns).

Overall, the market appears to price physical risks related to tropical cyclones. In "quiet" times, physical risk exposure is associated with a risk premium of about 2 percentage points. However, this premium seems to fade out during years of high cyclone activity, as the realization of cyclones (and the losses or expected losses associated to it) tend to affect stock prices negatively.

4.3 Heterogeneous effects

Sector-level risk premia

Exposure to cyclones may be more salient for firms in some sectors than others due to the nature of the physical assets they hold. Different types of assets can have different vulnerabilities to cyclones even though they are at the same location. Additionally, some types of assets can be easier to relocate or to apply adaptation measures. Therefore, one may expect different prices of cyclone risk for firms depending on their sector of activity. In this section, we look at how the market prices such risks separately in the Energy, Materials, and Utilities sectors.

Figure 4 shows that each sector is characterized by a distinct portfolio of physical assets. In the energy sector, mines, power plants, and refinery facilities account for 51%, 24%, and 19% of its assets, respectively. The materials sector is characterized by mines (70%), power plants (14%), and cement plants (7%). At the extreme, 99% of assets in the utilities sector are power plants.

We repeat the above analysis separately for each sector and report the results in Table 7. Columns 1, 3, and 5 show the estimates for the baseline regression in Table 4. We also introduce the interaction of exposure to cyclones and cyclone activity such as those in 6 in columns 2, 4 and 6. As expected, the impact of EAI on stock returns unconditional on cyclone activity is insignificant in all three sectors. When taking into account cyclone activity, the market seems to price cyclone exposure in the materials sector. For example, in the quietest year (the year 2022 when there are only 35 cyclones), one standard deviation higher cyclone exposure is associated with 0.18 percentage points higher monthly return. However, in the busiest year (the year 2020 when there are 51 cyclones), a one standard deviation higher exposure is associated with a 0.37 percentage point lower monthly return (respectively 2.2% and -0.7% annual returns). Note that in quiet times, the orders of magnitudes of cyclone risk premia are slightly higher in the energy sector and lower in the utilities sector.

One possible explanation for why the market only prices risks related to cyclones within the materials sector lies in the composition of assets in this sector. Mines and mining facilities which account for 70% of its assets are very difficult to relocate compared to other types of assets. For this reason, given the same exposure to cyclones (which mainly depends on assets' locations), firms that own mines and mining facilities as the majority of their assets are likely to be more negatively affected by cyclones. As a result, the market would require a higher risk premium for these firms.

Firms' heterogeneous exposure to cyclones

In this section, we investigate whether risks related to cyclones are priced differently depending on how exposed firms are to such risks. To this end, we split the sample into firms with high exposure and those with low exposure to cyclones and repeat the analysis as in Table 4 and Table 6.

Table 8 show the coefficients associated with the firm-level EAI in these sub-samples. A highly exposed firm is defined as one having an exposure higher than the median within its industry. Columns 1 and 3 show that the impact of EAI on stock return unconditional on cyclone activity is insignificant, as expected. When taking into account cyclone activity, for highly exposed firms, the impact of EAI on stock returns varies from -0.96 percentage points (in 2020) to 1.3 percentage points in monthly return (in 2022) for a one standard deviation higher exposure. For firms with low exposure, the impact of EAI on stock returns is independent of cyclone activity and remains insignificant.

Overall, these result suggest that risks related to cyclones seem to be only priced among firms that have high exposure. This is a plausible finding. Firms highly exposed to cyclones have a large proportion of their physical assets located in area of hazard, information about firms' exposure might be more salient to investors compared to firms with low exposure and hence make it easier for them to price this risk.

Firms' financial characteristics

In this section, we investigate whether the market prices exposure to physical risks differently depending on firms' characteristics. The first aspect we look at is profitability. Firms with substantial profits are likely to have more resources to engage in adaptation measures and therefore can be (or could become) more resilient to the impact of tropical cyclones. Therefore, one may expect the market to price differently climate physical risks depending on their profitability. In Panel A of Table 9, we split firms into two sub-samples according to their profitability and rerun the regressions 5 and 6. In this analysis, we use quarterly return on equity (ROE) as a measure of firms' ability to generate profits. The results suggest that the market only prices risks to cyclones among firms with low profitability, which is in line with our predictions.

Similarly, firms with high investment capacity are more likely to engage in adaptation measures and hence become less vulnerable to cyclones compared to those that are not. The market therefore may price this type of risk differently between these two types of firms. In Panel B of Table 9, we use the level of capital expenditure per dollar of asset (CAPEX/Total Asset) as a measure for firm investment and show the impact of EAI on stock returns on the two sub-samples splitted by its level of investment. Overall, the market seems to price physical risks related to cyclones in a similar ways for firms with high or low investment.

5 Conclusion

This paper proposes a bottom-up, forward-looking measure of cyclone risk exposure based on probabilistic assessment of damages to companies' physical assets. We estimate the average expected losses on physical assets due to hurricane (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). We then assess whether physical climate risk related to tropical cyclones is priced by the equity market. Cyclones-related risks have been shown to be the most destructive natural disaster worldwide in terms of dollar losses, and the number of such events has doubled since 1980 (Hoeppe (2016)). A clear advantage of our methodology with respect to commercially available physical risk scores (e.g. Moody's 427 scores) is the fact that our measure is transparent and replicable. It also allows to flexibly adjust the climate scenarios considered for the estimation.

We find that overall, and whatever the measure of firms' risk exposure we consider (expected annual impact or tail impact), cyclone risk does not seem to be priced by the market when considering the full sample period of interest (2016-2022). However, when interacting our hurricane exposure variable with a measure of overall cyclone activity, we find that a one standard deviation higher cyclone exposure is associated with a 2.2% higher annual return during "quiet" years, while it is associated with a -0.7% annual return during years of intense (above median) cyclone activity. Firms with high hurricane exposure, with lower profitability and lower investment are particularly affected. Overall, the market appears to price physical risks related to tropical cyclones. But the physical risk premium fades out during years of high cyclone activity, as the realization of cyclones (and the losses or expected losses associated to it) tend to affect stock prices negatively.

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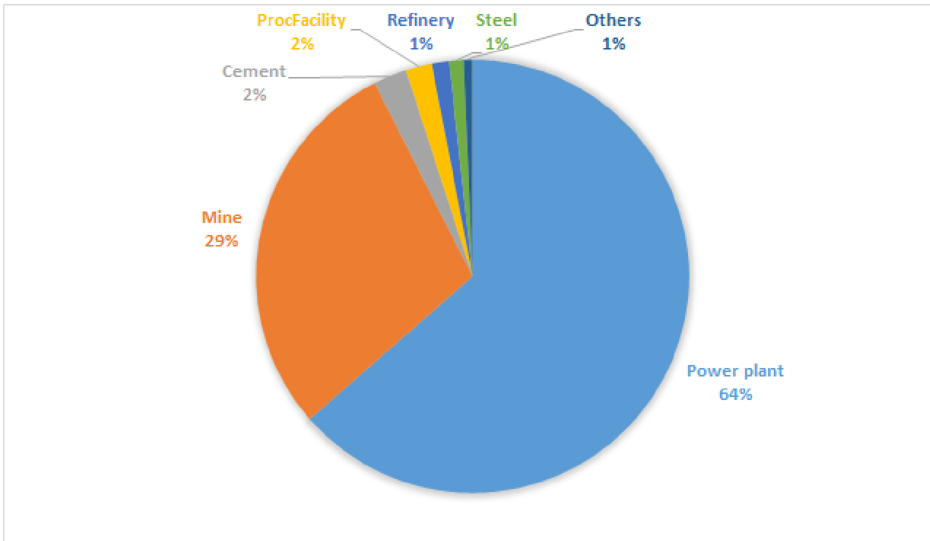
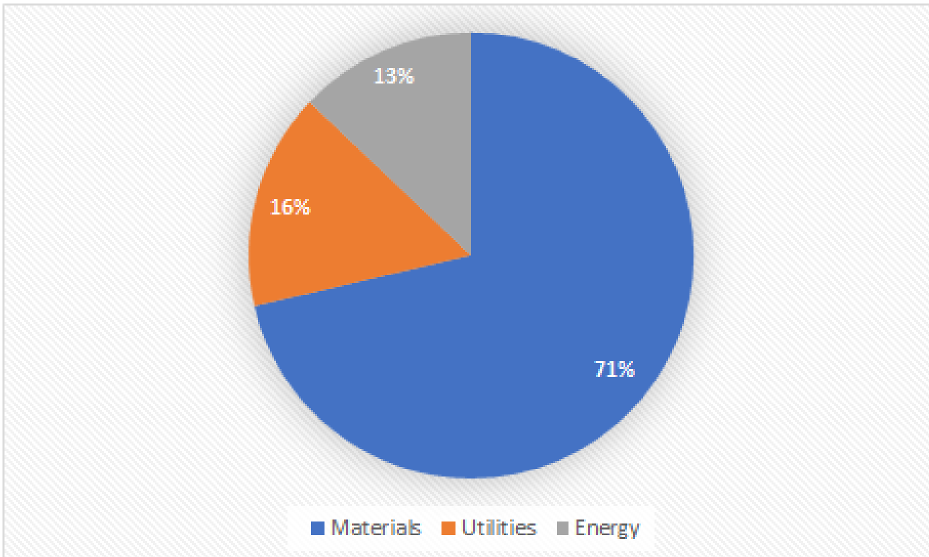
Figures and Tables

Figure 1: Distribution of Assets by asset type



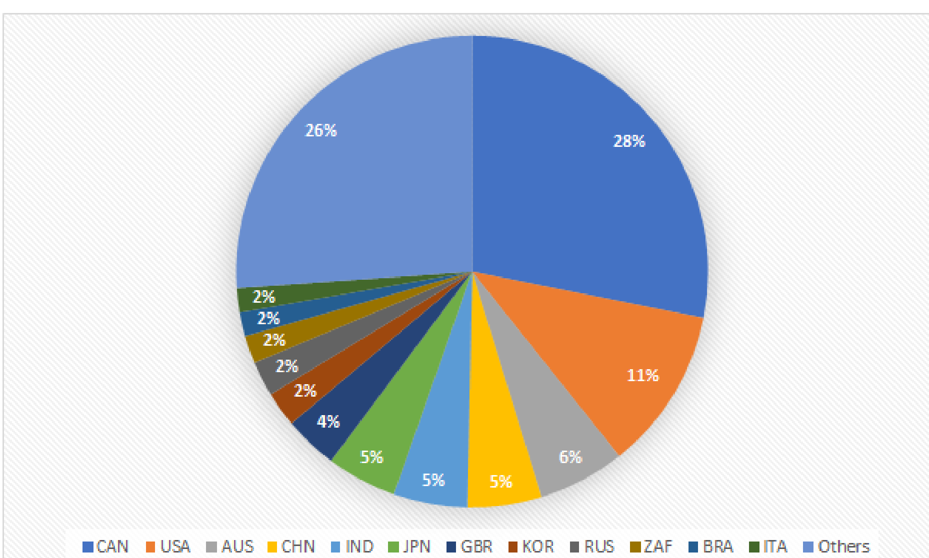
The pie chart presents the distribution of assets by asset type.

Figure 2: Distribution of firms by sector



The pie chart presents the distribution of firms by GICS two-digit sectors.

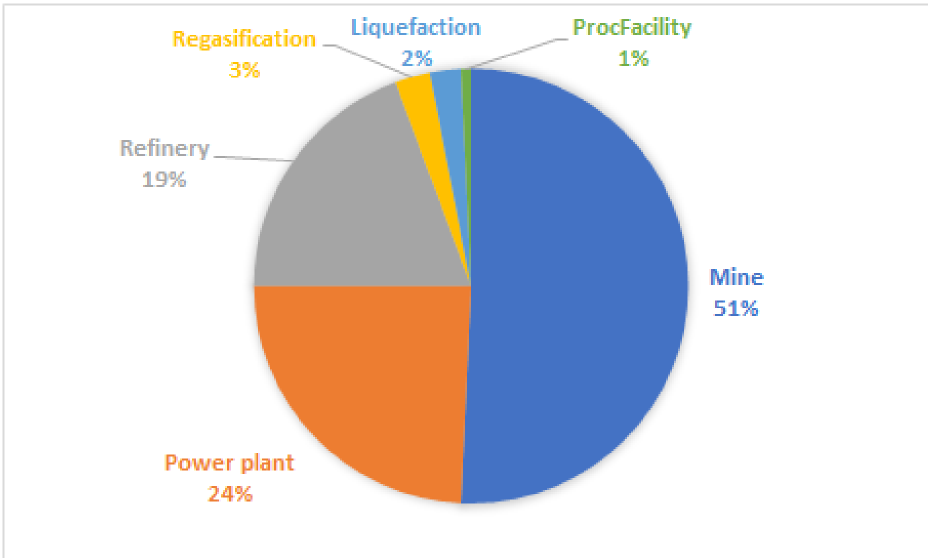
Figure 3: Distribution of firms by country



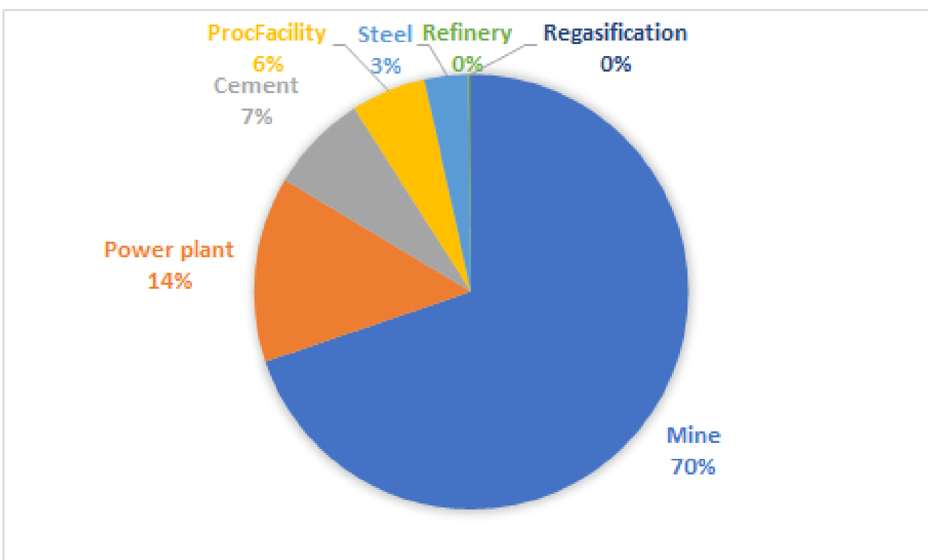
The pie chart presents the distribution of firms by country of incorporation in our sample.

Figure 4: Asset types by sector

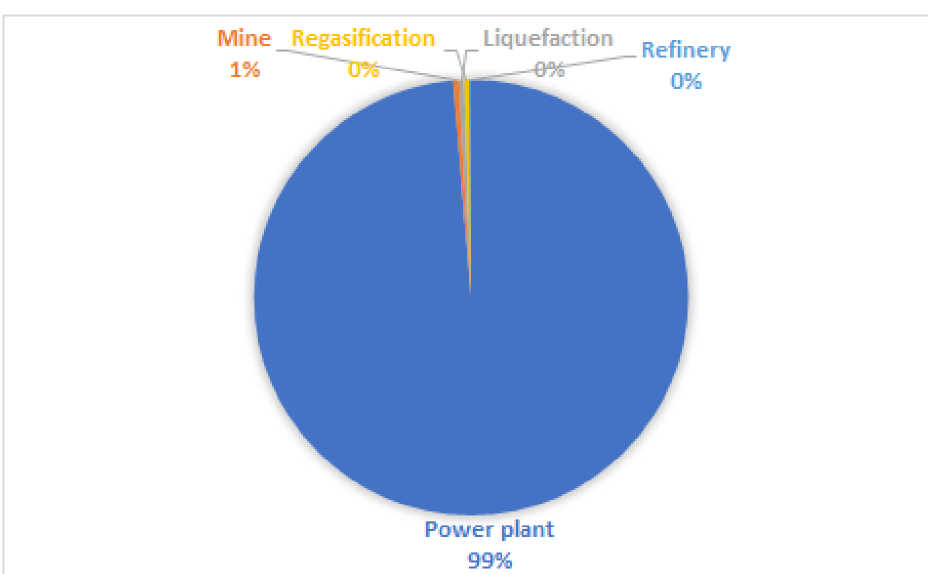
(a) Energy



(b) Materials

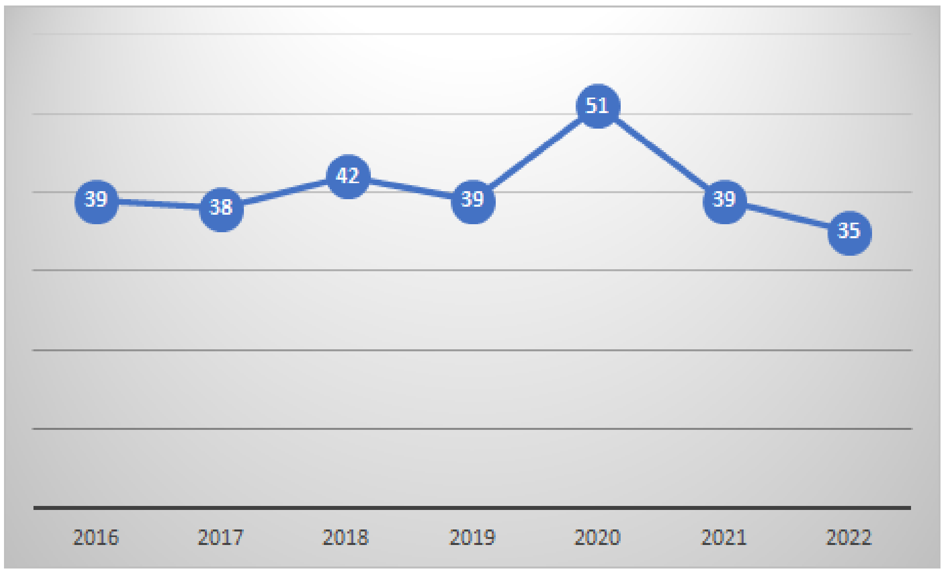


(c) Utilities



Subplot (a) presents the portfolio of physical assets in Energy sector (GICS code: 10). Subplot (b) presents the portfolio of physical assets in Materials sector (GICS code: 15). Subplot (c) presents the portfolio of physical assets in Utilities sector (GICS code: 55).

Figure 5: Number of hurricanes (Atlantic and North Pacific)



The plots show the number of tropical cyclones that occurred within the Atlantic, eastern Pacific, and central Pacific basins. Data is from the Tropical Cyclone Report (`https://www.nhc.noaa.gov/data/tcr/index.php`).

Table 1: Physical Risk Exposure by sector and country of incorporation

Panel A: Physical Damage 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	103	0.07	0.08	0.08	0.01	0.01	0.01
Materials	563	0.10	0.12	0.11	0.01	0.01	0.01
Utilities	124	0.14	0.15	0.15	0.02	0.02	0.02
Panel B: Physical Damage by country of incorporation							
		Expected Annual Impact (EAI)			Tail Impact (TI.RP50)		
Country	# of Firms	RCP2.6	RCP4.5	RCP6.0	RCP2.6	RCP4.5	RCP6.0
Highest exposure							
Taiwan	11	1.91	2.11	2.04	0.15	0.16	0.16
the Philippines	7	0.95	1.05	1.01	0.12	0.13	0.13
Japan	38	0.67	0.74	0.72	0.07	0.08	0.07
Jamaica	1	0.58	0.62	0.63	0.13	0.14	0.13
Luxembourg	1	0.34	0.55	0.47	0.07	0.09	0.08
South Korea	19	0.28	0.32	0.30	0.05	0.05	0.05
Cayman Islands	3	0.21	0.23	0.22	0.03	0.03	0.03
France	8	0.15	0.16	0.16	0.03	0.03	0.03
UK	29	0.14	0.15	0.15	0.01	0.01	0.01
Colombia	4	0.10	0.12	0.11	0.02	0.03	0.03
Lowest exposure							

(Continued on next page)

Table 1 – *(Continued from previous page)*

Romania	3	0.00	0.00	0.00	0.00	0.00	0.00
Saudi Arabia	6	0.00	0.00	0.00	0.00	0.00	0.00
Greece	3	0.00	0.00	0.00	0.00	0.00	0.00
Jordan	2	0.00	0.00	0.00	0.00	0.00	0.00
Türkiye	11	0.00	0.00	0.00	0.00	0.00	0.00
Egypt	4	0.00	0.00	0.00	0.00	0.00	0.00
Peru	4	0.00	0.00	0.00	0.00	0.00	0.00
Hungary	2	0.00	0.00	0.00	0.00	0.00	0.00
Austria	1	0.00	0.00	0.00	0.00	0.00	0.00
Guernsey	1	0.00	0.00	0.00	0.00	0.00	0.00

The table show the average expected annual impact (EAI) and Tail Impact (TI) for a return period of 50 years (TI.RP50) by sector (Panel A) and country (Panel B).

Table 2: Summary Statistics

Panel A: Physical Risk variables (as percentage of asset)					
Statistic	N	Mean	St. Dev.	Min	Max
EAI (RCP2.6)	67,806	0.079	0.343	0.000	5.286
EAI (RCP4.5)	67,806	0.089	0.376	0.000	5.788
EAI (RCP6.0)	67,806	0.086	0.366	0.000	5.630
TI.RP50 (RCP2.6)	67,806	0.011	0.032	0.000	0.289
TI.RP50 (RCP4.5)	67,806	0.012	0.034	0.000	0.313
TI.RP50 (RCP6.0)	67,806	0.012	0.034	0.000	0.305
TI.RP100 (RCP2.6)	67,806	0.009	0.024	0.000	0.203
TI.RP100 (RCP4.5)	67,806	0.010	0.026	0.000	0.220
TI.RP100 (RCP6.0)	67,806	0.010	0.026	0.000	0.215
TI.RP250 (RCP2.6)	67,806	0.009	0.021	0.000	0.162
TI.RP250 (RCP4.5)	67,806	0.010	0.023	0.000	0.176
TI.RP250 (RCP6.0)	67,806	0.010	0.022	0.000	0.172
Panel B: Stock returns and control variables					
RET (excess, monthly, in %, winsorized at 1%)	67,716	1.55	16.05	−33.53	64.63
SIZE (monthly, in log)	67,806	19.98	2.05	10.83	26.23
B/M (monthly, winsorized at 2.5%)	67,806	1.06	0.98	0.09	4.83
LEVERAGE (quarterly, winsorized at 2.5%)	67,806	0.16	0.16	0.00	0.57
INVEST/A (quarterly, winsorized at 2.5%)	67,806	0.04	0.05	0.00	0.20
ROE (quarterly, winsorized at 2.5%, in %)	67,806	−1.69	10.55	−44.04	15.17
PPE (quarterly, in log)	67,806	5.74	2.68	−7.22	12.40
MOM (monthly, in %)	67,806	1.92	5.49	−10.82	27.42
VOL (monthly, in %)	67,806	14.96	9.99	2.54	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 and VOL is the twelve-month rolling standard deviation. MOM and VOL is the average and standard deviation of the last twelve-month returns (month t included).

Table 3: Correlations between different measures of risk exposure

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)
1.0000	0.9996	0.9998	0.9146	0.9097	0.9117	0.8813	0.8748	0.8771	0.8414	0.8357	0.8378
0.9996	1.0000	1.0000	0.9165	0.9135	0.9149	0.8847	0.8797	0.8816	0.8459	0.8415	0.8431
0.9998	1.0000	1.0000	0.9159	0.9123	0.9139	0.8836	0.8781	0.8801	0.8444	0.8396	0.8414
0.9146	0.9165	0.9159	1.0000	0.9971	0.9985	0.9909	0.9848	0.9870	0.9678	0.9615	0.9636
0.9097	0.9135	0.9123	0.9971	1.0000	0.9998	0.9938	0.9923	0.9932	0.9752	0.9727	0.9737
0.9117	0.9149	0.9139	0.9985	0.9998	1.0000	0.9936	0.9907	0.9920	0.9737	0.9700	0.9714
0.8813	0.8847	0.8836	0.9909	0.9938	0.9936	1.0000	0.9980	0.9990	0.9922	0.9885	0.9899
0.8748	0.8797	0.8781	0.9848	0.9923	0.9907	0.9980	1.0000	0.9998	0.9937	0.9933	0.9937
0.8771	0.8816	0.8801	0.9870	0.9932	0.9920	0.9990	0.9998	1.0000	0.9936	0.9923	0.9930
0.8414	0.8459	0.8444	0.9678	0.9752	0.9737	0.9922	0.9937	0.9936	1.0000	0.9986	0.9993
0.8357	0.8415	0.8396	0.9615	0.9727	0.9700	0.9885	0.9933	0.9923	0.9986	1.0000	0.9999
0.8378	0.8431	0.8414	0.9636	0.9737	0.9714	0.9899	0.9937	0.9930	0.9993	0.9999	1.0000

Table 4: Expected Annual Impact (EAI) and Stock Returns

	RCP 2.6	RCP 4.5	RCP 6.0	RCP 2.6	RCP 4.5	RCP 6.0
EAI	−0.02	−0.01	−0.02	0.03	0.03	0.03
	(0.07)	(0.06)	(0.06)	(0.08)	(0.07)	(0.08)
Observations Observations	67,716	67,716	67,716	67,716	67,716	67,716
R^2	0.27	0.27	0.27	0.27	0.27	0.27
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 the expected annual impact (EAI) 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.

Table 5: Tail Impact and Stock Returns

	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	0.32	0.35	0.34	0.27	0.30	0.29	0.15	0.20	0.18
	(1.07)	(0.99)	(1.02)	(1.42)	(1.31)	(1.34)	(1.63)	(1.50)	(1.54)
Observations	67,716	67,716	67,716	67,716	67,716	67,716	67,716	67,716	67,716
R^2	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27
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 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.

Table 6: Risk exposure and stock returns, interaction with cyclone activity

Panel A: Number of cyclones

	RCP 2.6	RCP 4.5	RCP 6.0	RCP 2.6	RCP 4.5	RCP 6.0
EAI	4.49***	3.98***	4.13***	4.36***	3.87***	4.01***
	(1.12)	(0.98)	(0.97)	(1.12)	(0.97)	(1.01)
$EAI \times CYC.ACTV$	−0.11***	−0.10***	−0.10***	−0.11***	−0.09***	−0.10***
	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)
Observations	67,716	67,716	67,716	67,716	67,716	67,716
R^2	0.27	0.27	0.27	0.27	0.27	0.27
MonthYear FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y
Industry FE	N	N	N	Y	Y	Y

Panel B: High cyclone activity indicator

	RCP 2.6	RCP 4.5	RCP 6.0	RCP 2.6	RCP 4.5	RCP 6.0
EAI	0.49***	0.46***	0.47***	0.53***	0.49***	0.50***
	(0.18)	(0.17)	(0.17)	(0.17)	(0.15)	(0.16)
$EAI \times HIGH.ACTV$	−0.69**	−0.64**	−0.66**	−0.69***	−0.63***	−0.65***
	(0.28)	(0.25)	(0.26)	(0.27)	(0.25)	(0.25)
Observations	67,716	67,716	67,716	67,716	67,716	67,716
R^2	0.27	0.27	0.27	0.27	0.27	0.27
MonthYear FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y
Industry FE	N	N	N	Y	Y	Y

This table presents the cross-sectional regressions of monthly excess stock return on physical risk exposure (measured by EAI), its interaction with the number of cyclones (CYC.ACTV) in column Panel A or with an indicator for high cyclone activity (HIGH.ACTV, taking value of 1 if CYC.ACTV is above the sample median and 0 otherwise) in Panel B. Industry fixed effect is not included in columns 1 - 3 and included in columns 4 - 6. Controls, month-year, country of incorporation, industry fixed effects and the interaction of CYC.ACTV or HIGH.ACTV with these variables 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.

Table 7: Risk exposure and stock returns by sector

	Energy		Materials		Utilities	
EAI	0.55	6.74	0.05	4.02***	0.02	1.13
	(0.84)	(9.75)	(0.09)	(1.41)	(0.04)	(0.94)
$EAI \times CYC.ACTV$		−0.16		−0.10***		−0.03
		(0.23)		(0.04)		(0.02)
Observations	7,737	7,737	50,551	50,551	9,428	9,428
R^2	0.34	0.35	0.29	0.30	0.25	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 physical risk exposure (measured by EAI in scenario RCP 4.5) and its interaction with the number of cyclones (CYC.ACTV). Controls, month-year, country of incorporation, industry fixed effects and the interaction of CYC.ACTV with these variables 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.

Table 8: Physical Risk and Stock Returns, High versus Low Exposure

	High Exposure		Low Exposure	
EAI	0.02	4.14***	1.27	8.74
	(0.09)	(1.06)	(2.68)	(18.57)
$EAI \times CYC.ACTV$		−0.10***		−0.12
		(0.03)		(0.45)
Observations	33,587	33,587	34,129	34,129
R^2	0.28	0.28	0.26	0.26
MonthYear FE	Y	Y	Y	Y
Country FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y

This table presents the cross-sectional regressions of monthly excess stock return on physical risk exposure (measured by EAI in scenario RCP 4.5) and its interaction with the number of cyclones (CYC.ACTV). High Exposure is the sub-sample of companies whose EAI is above the within-industry median and Low Exposure is the one whose EAI is below the within-industry median. Controls, month-year, country of incorporation, industry fixed effects and the interaction of CYC.ACTV with these variables 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.

Table 9: Physical Risk, Stock Returns, and Firm characteristics

Panel A: High versus low profitability

	High ROE		Low ROE	
EAI	−0.02	1.51	0.02	4.77***
	(0.14)	(1.52)	(0.12)	(1.82)
$EAI \times CYC.ACTV$		−0.04		−0.12**
		(0.04)		(0.05)
Observations	34,187	34,187	33,529	33,529
R^2	0.28	0.28	0.27	0.27
MonthYear FE	Y	Y	Y	Y
Country FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y

Panel B: High versus low investment

	High investment		Low investment	
EAI	−0.24	4.19**	0.22**	3.40***
	(0.16)	(2.02)	(0.11)	(1.21)
$EAI \times CYC.ACTV$		−0.11**		−0.08**
		(0.05)		(0.03)
Observations	34,155	34,155	33,561	33,561
R^2	0.28	0.28	0.26	0.27
MonthYear FE	Y	Y	Y	Y
Country FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y

This table presents the cross-sectional regressions of monthly excess stock return on physical risk exposure (measured by EAI in scenario RCP 4.5) and its interaction with the number of cyclones (CYC.ACTV). In Panel A, High ROE is the sub-sample of companies whose return on equity is above the within-industry median and Low Exposure is the one whose return on equity is below the within-industry median. In Panel B, High investment is the sub-sample of companies whose investment/total asset is above the within-industry median and Low investment is those whose investment/total asset is below the within-industry median. Controls, month-year, country of incorporation, industry fixed effects and the interaction of CYC.ACTV with these variables 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.

APPENDIX

Following the computation in ECB report on climate risk and financial stability, `https://www.ecb.europa.eu/pub/pdf/other/ecb.climateriskfinancialstability202107_annex~4bfc2dbc5e.en.pdf`.

1. Calculation of the "probability of exceedance" $P_{e,RP}$ in a given year, indicating the probability that a cyclone with a given return period (RP, in years) takes place, $P_{e,RP} = 1/RP$.

2. Calculation of the "probability of occurrence" in one year, p_{RP}:

   $p_{250} = P_{e,250}$

   $P_{e,100} = 1 - (1 - p_{250})(1 - p_{100})$, so $p_{100} = 1 + (P_{e,100}–1)/(1–p_{250})$

   $P_{e,50} = 1 - (1 - p_{250})(1 - p_{100})(1 - p_{50})$, so $p_{50} = 1 + (P_{e,50}–1)/((1–p_{250})(1–p_{100}))$