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# An Empirical Assessment of the Financial Impacts of Climate-related Hazard Events

**Abstract**

This empirical study quantifies corporate valuation and credit impacts of climate-related hazard events, particularly cyclones, storms, and droughts. We find statistically and economically significant negative impacts of hazard events on the subsequent valuation of affected firms, which increase with firms' facility exposure to impacted geographical areas. The effect on firm valuation, measured by asset or equity returns, can be as large as 2.9% over the first ten weeks post-event. Our analysis relies on historical event data and facility exposures from Moody's climate risk assessment affiliate Four Twenty Seven and external sources, as well as on Moody's Analytics corporate valuation data and EDF™ (Expected Default Frequency) credit measures. Relative to the existing literature, our study has a broader firm and hazard type coverage expanding to non-U.S. firms and events.

Applications of this unique, empirical study can be very broad. Our focus is twofold: first, to translate the impact of climate-related hazard events into firms' credit quality; and second, to quantify common exposures to future climate-related hazard events across corporate entities. The ultimate goal of these applications is to measure credit portfolio concentration risks, namely, the range of correlated credit and ESG risks including climate risks. These new concentration risk measures can then be tied to credit portfolio management, e.g., quantifying climate hazards in credit loss forecasts, risk-based limits, value at risk, and/or capital frameworks.

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## 1. Introduction

The severity and frequency of climate-related hazards, such as cyclones and droughts, have been increasing substantially around the globe during the past few decades.<sup>1</sup> Ten of the 15 most active North Atlantic hurricane seasons since 1950 have occurred during the past 15 years, and 2020 is the sixth consecutive year when 10 or more multi-billion-dollar hazard events hit the U.S.<sup>2,3</sup> Businesses in areas affected by these events often face non-negligible losses and business disruptions. For example, 2017's Hurricane Maria wreaked devastation across Puerto Rico, a major U.S. pharmaceutical hub, leading to billions of lost revenues and a number of medication shortages.<sup>4</sup> In 2016, the European heatwaves slowed the economy and were largely responsible, for example, for the reported 10% year-over-year fall in H&M profit in Q3 due to slow sales.<sup>5</sup> The proliferation of these and many other climate-related hazards emerges as a novel — and increasingly important — corporate risk factor that warrants quantification.

In this paper, we quantify the impacts of climate-related hazard events on exposed public firms' valuation, measured by equity or asset returns. We proxy exposures to hazard events using firms' facility locations, focusing on three primary hazards: cyclones (hurricanes and typhoons), storms (tornadoes, hailstorms, thunderstorms, extratropical storms, etc.), and droughts. We leverage a unique dataset that covers global corporate facility locations compiled by Moody's affiliate Four Twenty Seven, along with hazard data from Four Twenty Seven and Emergency Events Database (EM-DAT<sup>6</sup>), as well as Moody's Analytics repository of data on asset and equity returns.

We find statistically and economically significant negative impacts of hazard events on the subsequent valuation of affected firms, which increase with firms' facility exposure to event areas. For instance, the effect on firm valuation, measured by excess asset or equity returns, can be as large as 2.9% over the first ten weeks post-event. A series of robustness checks demonstrate that our conclusions are not sensitive to variations in the empirical approach, including, but not limited to, adjusting the definition of excess returns and limiting the sample to U.S. firm-event pairs only.

We conclude by highlighting two applications of the event study. The first application translates our estimates of corporate valuation impacts into credit risk as measured by EDF<sup>TM</sup> (Expected Default Frequency) impacts under different future climate policy scenarios from the Network of Central Banks and Supervisors for Greening the Financial System (NGFS). As per the Bank of England's Biannual Exploratory Scenario, in the absence of policy changes, the worst-case scenario of global warming of four degrees Celsius by 2050 implies around a 37% increase in default probability at this horizon (mean in a diversified portfolio). The second application illustrates, in a portfolio-management context, the heterogeneous exposures to climate-related hazard events across firms from different countries, industries, and size groups.

We make several substantial contributions to the limited literature focused on climate-related hazard event effects on corporate valuation. The primary focus of existing studies has been on North Atlantic cyclones<sup>7</sup>; we evaluate other types of storms and droughts in other areas, expanding both the hazard type and the geographical coverage. To the best of our knowledge, our study is the first to use firm facility location data to proxy the magnitude of exposure to hazard events and to document the negative relationship between corporate valuation and the degree of exposure. Finally, we discuss novel applications linking the results of the event study to credit quality and concentration issues.

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<sup>1</sup> Henry Fountain, "[Climate Change Is Making Hurricanes Stronger, Researchers Find](#)," *New York Times*, May 18, 2020. James P. Kossin et al., "[Global Increase in Major Tropical Cyclone Exceedance Probability Over Past Four Decades](#)," Proceedings of the National Academy of Sciences of the United States of America, May 18, 2020. Jason Daley, "[Climate Change Has Made Droughts More Frequent Since 1900](#)," *Smithsonian Magazine*, May 2, 2019. Kate Marvel et al., "[Twentieth-Century Hydroclimatic Changes Consistent with Human Influence](#)," *Nature*, May 2, 2019.

<sup>2</sup> U.S. National Oceanic and Atmospheric Administration (NOAA) defines North Atlantic Hurricane Seasons as "extremely active" when the total seasonal activity measured by the Accumulated Cyclone Energy (ACE) is above 165% of the 1981–2010 median, [link](#).

<sup>3</sup> NOAA National Centers for Environmental Information, "[Billion-Dollar Weather and Climate Disasters: Overview](#)," October 7, 2020.

<sup>4</sup> Puerto Rico hosts 12 of the top-20 global pharmaceutical corporations. For media coverage of Hurricane Maria's impact on the pharmaceutical sector, see: Lisa M. Jarvis, "[Hurricane Maria's Lesson for the Drug Industry](#)," *Chemical & Engineering News*, September 17, 2018; Eric Palmar, "[Baxter Expects \\$70M Sales Hit from Hurricane Damage; Amgen Says Costs Could Top \\$165M](#)," *Fierce Pharma*, October 25, 2017.

<sup>5</sup> Clare Hutchinson, "[H&M Warns of Challenges Ahead as Late Heatwave Has It Sweating](#)," *Evening Standard*, September 30, 2016.

<sup>6</sup> EM-DAT, CRED / UCLouvain, Brussels, Belgium – [www.emdat.be](#) (D. Guha-Sapir).

<sup>7</sup> See e.g., Barrot and Sauvagnat (2016), Dessaint and Matray (2017), Kruttli et al. (2019), and Lanfear et al. (2020).

## 2. Empirical Design and Data

### 2.1 Returns and Expected Returns

The primary question we address in this study is whether hazard-impacted firms exhibit changes in valuation systematically different than unimpacted firms. We measure impacts on corporate valuation using weekly asset or equity returns from Moody's Analytics data repository. While equity returns are observable, asset returns are a measure of changes in the market value of assets produced by the Moody's Analytics EDF model.<sup>8</sup>

For each firm-hazard event pair, we calculate cumulative excess post-event returns. Excess returns are the difference between actual returns and expected returns. As common in the event study literature, we construct expected post-event weekly returns using the Fama and French (1996) three-factor model:

$$r_{i,t} - r_t^f = \alpha_i + \beta_i' r_{factor,t} + \epsilon_{i,t}.$$

Here  $r_{i,t}$  denotes firm  $i$ 's weekly asset returns and  $r_t^f$  denotes the risk-free rate (three-month Treasury bill rate). The factors included in  $r_{factor,t}$  are the global market factor (defined as the global weighted average return in excess of the risk-free rate  $r_t^f$ ), the size factor (defined as the average return on firms in the largest tercile less that of firms in the smallest tercile), and the book-to-market factor (defined as the average return of firms in the bottom tercile of the book-to-market value of assets, less that of firms in the top tercile). The model is estimated using a rolling regression starting 75 weeks before the event.<sup>9</sup> We winsorize the estimates of factor loadings at the top and bottom 2.5%, as is common in the climate event-related literature.

We then use the estimated  $\alpha_i$  and  $\beta_i'$  along with factor realizations to construct post-event expected returns:

$$E(r_{i,t}) = r_t^f + \hat{\alpha}_i + \hat{\beta}_i' r_{factor,t}$$

Finally, we cumulate the above excess returns up to  $h$  weeks post-event to obtain cumulative expected returns for use in our empirical exercises below:

$$E(r_{i,t \rightarrow t+h}) = \prod_{\tau=t-1}^{t+h} (E(r_{i,\tau}) + 1) - 1$$

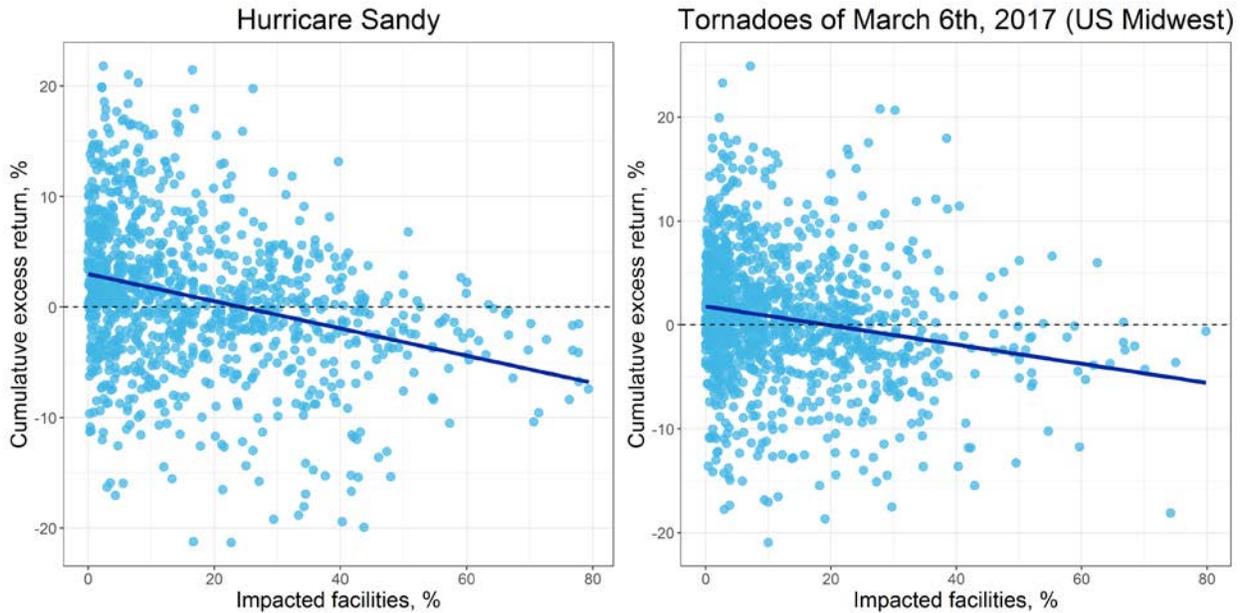
### 2.2 Regression Specification

Our primary empirical exercise assesses the relation between firms' exposure to hazard events and the subsequent dynamics of their excess returns. We measure a firm's exposure to hazard events by the share of its facilities in an event region (henceforth, "impacted facilities"). Our intuition is as follows: the larger the share of impacted facilities, the larger the potential physical damage to a firm's operations, which should be reflected by a firm's asset return dynamics. A quick look at the data supports this conjecture. Figure 1 plots the relation between cumulative excess returns and the share of impacted facilities for firms hit by two hazard events: Hurricane Sandy in fall 2012 and a series of tornadoes in the American Midwest in spring 2017. We find the mean 10-week cumulative post-event excess asset return for firms with less than 10% facilities impacted by Hurricane Sandy is around 1.5%; whereas, the return is -1.7% for firms with more than 30% facilities impacted.

<sup>8</sup> See Pooya Nazeran and Douglas Dwyer, "Credit Risk Modeling of Public Firms: EDF9," Moody's Analytics, June 2015.

<sup>9</sup> We end the estimation sample three weeks before the event, to ensure that event-induced returns don't impact the estimates of expected returns. We require at least 70 pre-event observations; the number varies slightly because asset returns are sometimes reported at irregular frequencies, due to public holidays, etc.

Figure 1 Asset returns of impacted firms 10 weeks post-event.



Our baseline empirical specification is the following firm-level panel regression:

$$r_{i,t-1 \rightarrow t+h} - E(r_{i,t-1 \rightarrow t+h}) = \gamma_h + \delta_h \cdot \text{Impacted}_{i,t} + \epsilon_{i,t+h},$$

where  $r_{i,t-1 \rightarrow t+h} - E(r_{i,t-1 \rightarrow t+h})$  is firm  $i$ 's cumulative excess return over the  $h$ -week horizon after the event, and  $\text{Impacted}_{i,t}$  is the share of firm  $i$ 's facilities located in the geographic area hit by a hazard event at time  $t$ , with  $\text{Impacted}_{i,t} = 0$  corresponding to the group of unimpacted firms. We double-cluster standard errors at the firm- and date-level.

The coefficient of interest  $\delta_h$  can be interpreted as the effect of hazard events on excess returns of firms per 1% of their facilities impacted. Estimating the above relation at horizons  $h > 0$  produces a set of coefficients  $\{\delta_h\}_{h=0:H}$  that illustrates the dynamics of this effect in time. We let  $h$  vary between 0 and 13 weeks, as there is little theoretical guidance about how long it takes for the hazard impact to be incorporated into asset prices, and report results from all those horizons below. Since the occurrence and location of hazard events may be predictable at short horizons, we start excess return accumulation one week before the hazard events.<sup>10</sup>

### 2.3 Hazard Event Data

We use data covering dates and locations of hazard events from two sources: Four Twenty Seven and EM-DAT. Four Twenty Seven provides a proprietary data set that tracks the impact of climate hazard events on global firms.<sup>11</sup> We complement this cyclone data with the data from EM-DAT also covering droughts and other types of storms. EM-DAT is a hazard event database maintained by the Centre for Research on the Epidemiology of Disasters (CRED) at the Université Catholique de Louvain. EM-DAT is more macro-oriented and reports economic damages from events, which we use to rank impact severity. Event locations are reported at the level of subnational administrative units. For example, landfall areas of U.S. cyclones are reported at the state or county levels.

Among the hazard events covered by Four Twenty Seven and EM-DAT, we focus on a subset that: (1) occurred between 2000 and 2018; (2) resulted in at least \$1B in economic damage (in 2019 USD) as assessed by EM-DAT; and (3) were among the top-10 events for the relevant hazard type, where the ranking is based on the following three criteria:

<sup>10</sup> In particular, the U.S. NOAA predicts North Atlantic cyclone paths up to a five-day horizon (NOAA, 2017), and other weather events are predictable up to 10 days in advance (Voosen, 2019).

<sup>11</sup> Specifically, Four Twenty Seven links an external cyclone database from the World Meteorological Organization (WMO) to its database of global facility locations. The WMO database in turn use the NOAA as one of its input sources, which indicates that our results will be comparable to U.S.-focused research using NOAA data.

- » *Economic damage*: events with larger aggregate damage are also likely to cause greater losses to companies.
- » *Recency*: more recent events are likely to be associated with less noise, since we only have a snapshot of facility locations, and since the coverage of the asset return data improves over time.
- » *Noteworthiness*: events receiving greater attention in public sources are likely to be associated with greater losses to firms.

Specifically, we construct the following event index:

$$Index_{Event} = EconomicDamage_{Event} + Mean_{Hazard}(EconomicDamage_{Event}) * (Dummy_{Wiki} + Dummy_{2017-2018}),$$

where  $Dummy_{2017-2018}$  and  $Dummy_{Wiki}$  are dummy variables for hazard events that happened between 2017 and 2018, and that are covered in Wikipedia, respectively. We then rank events using this index and choose the top-10 events by hazard type.

In this paper, we focus on three specific hazard types: cyclones (hurricanes and typhoons), other types of storms, and droughts.<sup>12 13</sup> We use the event index to select top-10 events in each hazard category. See the Appendix for a list of selected events. The events in our sample took place between 2003 and 2018. There are events from all continents, though most of them happened in the U.S. Our decision to focus on the most prominent hazard events is motivated by two considerations. First, these events are more likely to affect many firms and to have a significant impact on their performance. As such, it increases our ability of detecting a meaningful difference between impacted and unimpacted firms. Second, estimates based on the recent, most devastating events are likely to be more representative of future events, as the frequency of severe climate-related hazard events intensifies.

## 2.4 Facility Location Data

Locations of firms' global facilities are collected by Moody's Analytics subsidiary Four Twenty Seven and are reported at the city level.<sup>14</sup> Since this data is a snapshot of firms' facility locations in 2019 Q3, we implicitly assume that it is representative for the whole period of the study (2000–2018).

We use the intersection of facility locations and hazard event locations to measure firms' exposure to hazard events. We classify a facility as impacted by a hazard event, if located in the event region. For each firm, we calculate the share of its facilities impacted, which we use as an exposure measure in our empirical study. We label a firm as impacted if it has at least some facilities impacted. Firms with no facilities in the event region enter the control group and are labeled as unimpacted. There are 16,874 impacted firm-event pairs in our sample across 30 events of the three hazard types; see the Appendix for more details. Figure 2 shows the distribution of impacted firm-event pairs by country of firms' headquarters. Although around half of our observations come from U.S. firms, the set has broad geographical coverage.

Figure 3 shows the distribution of impacted firm-event pairs by the hazard type and the share of exposed facilities. We see that across event dates in our sample, about 15% of firms are labeled as impacted. However, the distribution of the facility share exposed is highly skewed, with most observations located in the single-digit region. Our data limits us from directly observing if a firm suffered actual losses or business disruptions due to an event. As a result, we use the overlap between facility locations and hazard event regions as a proxy, implicitly focusing on the physical damage from hazard events.<sup>15</sup>

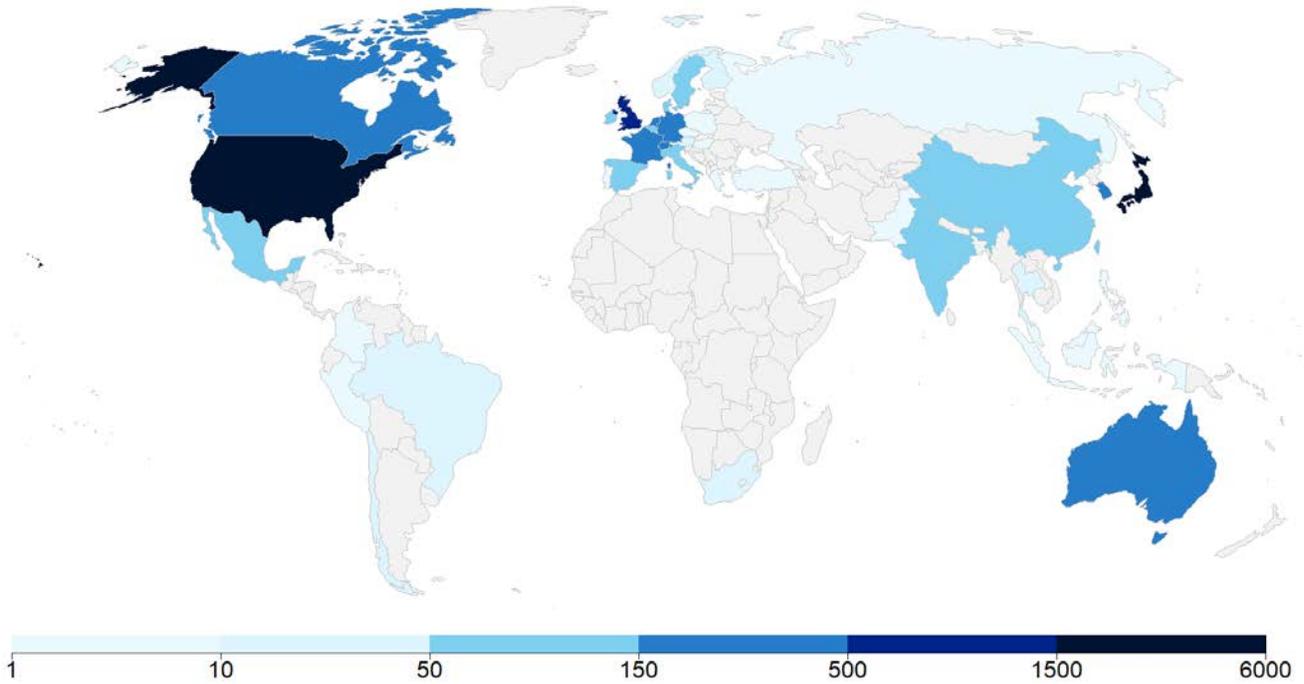
<sup>12</sup> U.S. NOAA defines a tropical cyclone as "a rotating, organized system of clouds and thunderstorms that originates over tropical or subtropical waters and has a closed low-level circulation." Depending on its strength, a tropical cyclone is classified as a tropical depression, a tropical storm, or a hurricane. Severe tropical cyclones that develop in the Northwestern Pacific Basin are called typhoons. Other types of storms include but are not limited to tornadoes, hailstorms, thunderstorms, and extratropical storms.

<sup>13</sup> See e.g., the IPCC report Seneviratne et al. (2012) for an overview of the literature linking these and other natural hazard events to climate change. The strength of the connection varies across hazard type and geography.

<sup>14</sup> In turn, Four Twenty Seven leverages facility location data from D&B Hoovers and Industrial Information Resources.

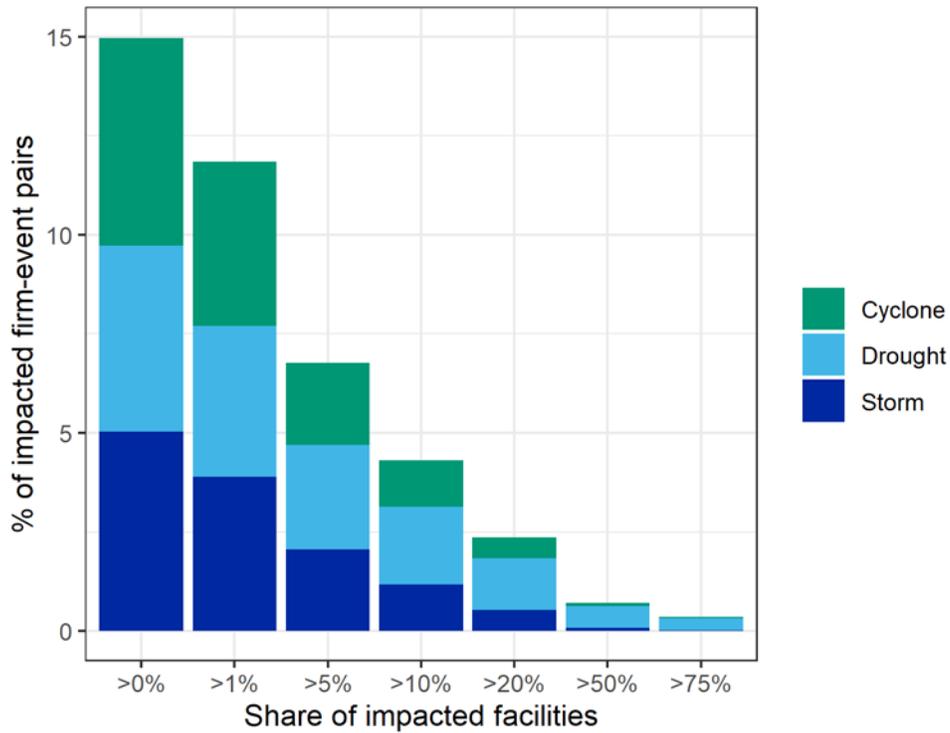
<sup>15</sup> This proxy potentially leaves out general equilibrium effects that might affect a wider firm population. For instance, hazard events can negatively affect firms outside of the event region through supply chain linkages; see, for example, Barrot and Sauvagnat (2016).

Figure 2 Distribution of impacted firms by country of headquarters.



Note, distribution of unique impacted firm-event pairs (16,874 in total).

Figure 3 Share of hazard-hit firms, distribution by hazard type, and the percentage of facilities impacted.



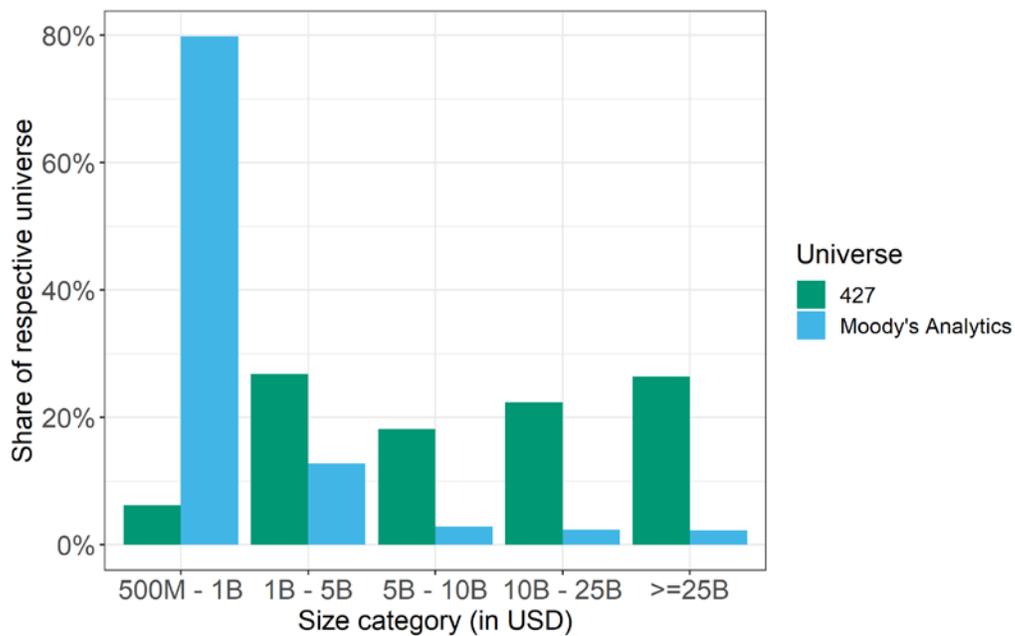
Note, the total number of unique firm-event pairs is 112,760.

## 2.5 Company Coverage

We complement the hazard event and facility location data with asset and equity returns from Moody's Analytics data repository. Our final firm sample is the intersection of Moody's Analytics and Four Twenty Seven databases, which includes approximately 2,200 of the largest public firms globally. Figure 4 compares firm-size distributions of Four Twenty Seven and Moody's Analytics datasets, in which the firm size is defined as sales for non-financial firms and total assets for financial firms. The figure illustrates that firms assessed by Four Twenty Seven tend to have a larger size than an average public firm. For instance, most firms in Moody's Analytics data have a size less than \$500M, while most firms in Four Twenty Seven data are above this threshold.

Since our sample's firm-size distribution skews toward large public firms, we believe our excess return impact estimates are conservative. Large firms are likely to be more resilient to climate-related hazard events due to better diversification, planning, and insurance coverage, among other things.

Figure 4 Firm-size distribution of 427 and Moody's Analytics public firm data.



Note, firm size is defined as sales for non-financial firms and total assets for financial firms.

### 3. Main Results

We find statistically and economically significant negative effects of hazard events on the subsequent valuation of impacted firms. To begin with, it is instructive to simply compare the average valuation dynamics across firm groups. Table 1 compares average excess equity returns of unimpacted firms with those of impacted firms that have more than 25% or 50% of their facilities exposed to events in our sample. This illustrates a large difference between the two groups of firms and suggests that climate-related hazard events can have non-negligible negative effects on firms' performance, which we investigate further using econometric analysis. This table shows results at the 10-week horizon as an example; however, below we show consistent results from all horizons between 0 and 13 weeks post-event.

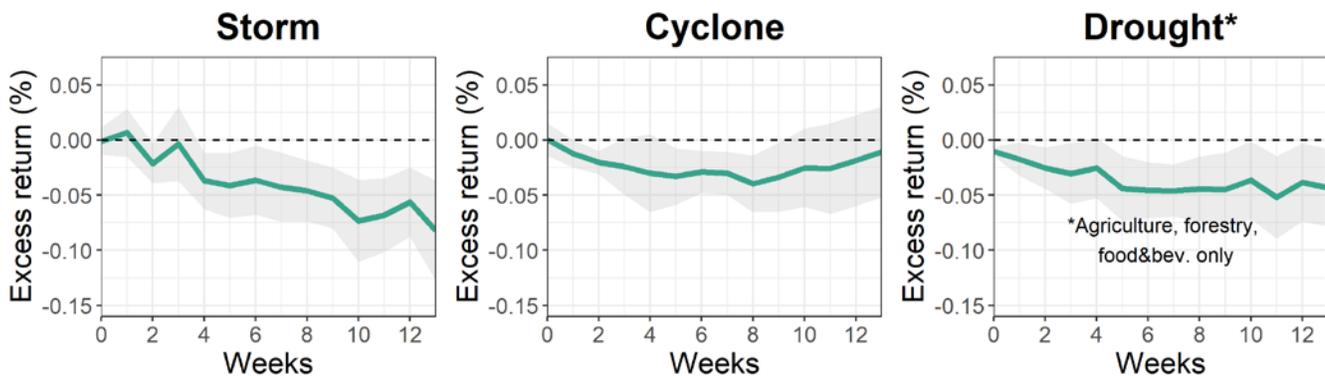
**Table 1** Mean Cumulative Post-event Excess Equity Returns at a 10-week Horizon

|          | UNIMPACTED FIRMS | IMPACTED FIRMS          |                         |
|----------|------------------|-------------------------|-------------------------|
|          |                  | >25% FACILITIES EXPOSED | >50% FACILITIES EXPOSED |
| Storm    | 0.70%            | -1.97%                  | -5.25%                  |
| Cyclone  | -0.14%           | -2.54%                  | -3.33%                  |
| Drought* | -0.87%           | -1.42%                  | -3.51%                  |

Note, \*Agriculture, Forestry, and Food and Beverage industries only.

Figures 5 and 6 present our main results based on the empirical design described in Section 2. The charts plot cross-sectional responses of cumulative excess returns to hazard event exposure, up to 13-weeks post-event. We identify a statistically and economically significant negative relation between firm facility exposure to hazard events and post-event excess returns. Note, for droughts, we present results only for firms in the agriculture, forestry, and food and beverage industries, for which we uncover the strongest signal as expected based on existing research (Hong, Li, and Xu, 2019).

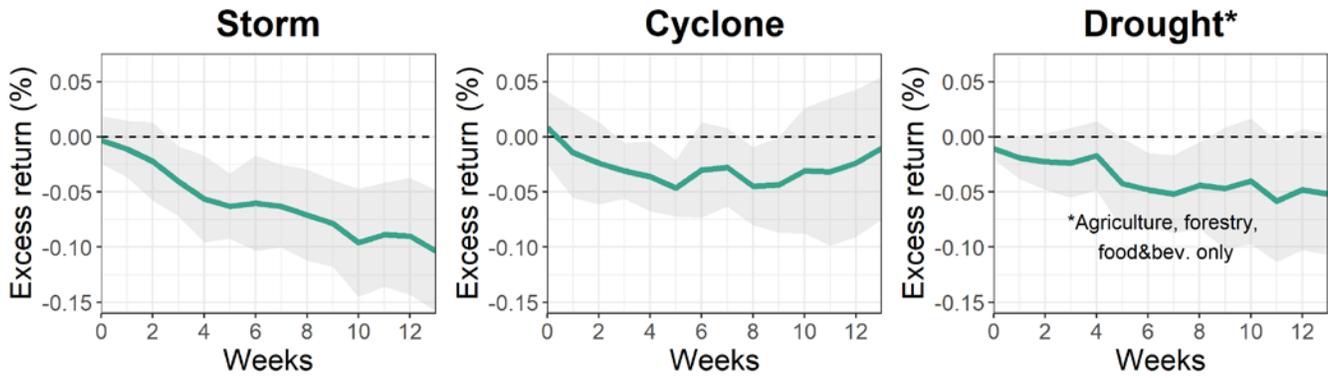
**Figure 5** Cumulative effect on post-event excess asset returns (per 1% of facilities impacted).



Note, the shaded area corresponds to 95% confidence interval.

Since our exposure measure is the share of the firm's facilities in the event region, these estimates quantify excess return impacts per 1% of facilities exposed. To translate them into total effects, one needs to factor in the degree of exposure. For instance, an average firm exposed to a storm in our sample has 7.1% of its facilities impacted. Given the estimated sensitivity of excess asset returns of -0.073% at a 10-week horizon, this exposure translates into a -0.52% impact on excess returns. Since the distribution of the share of facilities impacted is highly skewed to the left, as Figure 3 shows, it is also worth considering some of the most impacted firms for illustrative purposes. A 95<sup>th</sup> percentile firm exposed to a storm in our sample has 27.3% of impacted facilities, which implies a cumulative impact on excess asset returns of -1.99% at a 10-week horizon. Note, effects are slow to materialize, as seen by the magnitude of the estimates generally increasing by horizon in the figures. These patterns are consistent with the full extent of damage/impact not being evident immediately after the event and, instead, being priced in gradually.

Figure 6 Cumulative effect on post-event excess equity returns (per 1% of facilities impacted).



Note, the shaded area corresponds to 95% confidence interval.

Figure 6 plots the results of the same event study based on excess equity returns as a measure of changes in firms' valuation. Using this outcome variable makes our estimates more comparable to the results of the literature, which predominantly relies on equity returns. In addition, it verifies that our results are not driven by potential measurement errors in the asset return estimation. Equity return impacts are slightly larger than asset return impacts, which is expected given that equity can be seen as a leveraged position in a firm's assets. Table 2 further illustrates excess return impacts implied by our estimates across hazard types.

Table 2 Impacts on Post-event Excess Returns at a 10-week Horizon

|          | IMPACT PER 1% OF FACILITIES EXPOSED |                | SHARE OF FACILITIES EXPOSED |                 | TOTAL IMPACT  |                 |                |                 |
|----------|-------------------------------------|----------------|-----------------------------|-----------------|---------------|-----------------|----------------|-----------------|
|          | ASSET RETURNS                       | EQUITY RETURNS | MEAN                        | 95th PERCENTILE | ASSET RETURNS |                 | EQUITY RETURNS |                 |
|          |                                     |                |                             |                 | MEAN          | 95th PERCENTILE | MEAN           | 95th PERCENTILE |
| Storm    | -0.073%                             | -0.096%        | 7.1%                        | 27.3%           | -0.52%        | -1.99%          | -0.69%         | -2.62%          |
| Cyclone  | -0.025%                             | -0.031%        | 7.7%                        | 30.8%           | -0.19%        | -0.77%          | -0.24%         | -0.95%          |
| Drought* | -0.036%                             | -0.040%        | 15.8%                       | 72.7%           | -0.57%        | -2.62%          | -0.63%         | -2.92%          |

Note, \*Agriculture, Forestry, and Food and Beverage industries only.

## 4. Robustness

We carry out various robustness analyses. The first restricts our sample to U.S. firms and U.S. hazard events only. The second considers different specifications for expected post-event returns, against which we compare actual return realizations. The third studies responses of excess returns at longer horizons. Finally, we compute regression estimates with country and industry fixed effects. The following sections detail these analyses. We find our results remain robust to the alternative risk benchmarks.

### 4.1 U.S. Events and U.S. Firms Only

We provide estimates based on the sample restricted to U.S. firms and hazard events. This exercise improves the comparability of our results to those of the literature, which is mostly U.S.-centric. Figures 7 and 8 compare the results for both equity and asset returns.

Figure 7 Cumulative effect on post-event excess asset returns (per 1% of facilities impacted), U.S. firm-event pairs only.

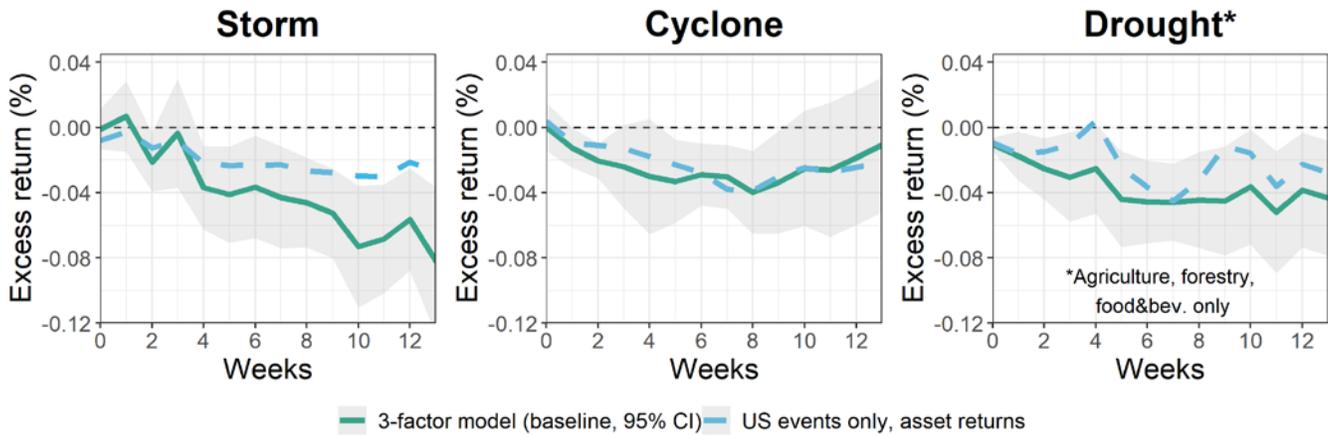
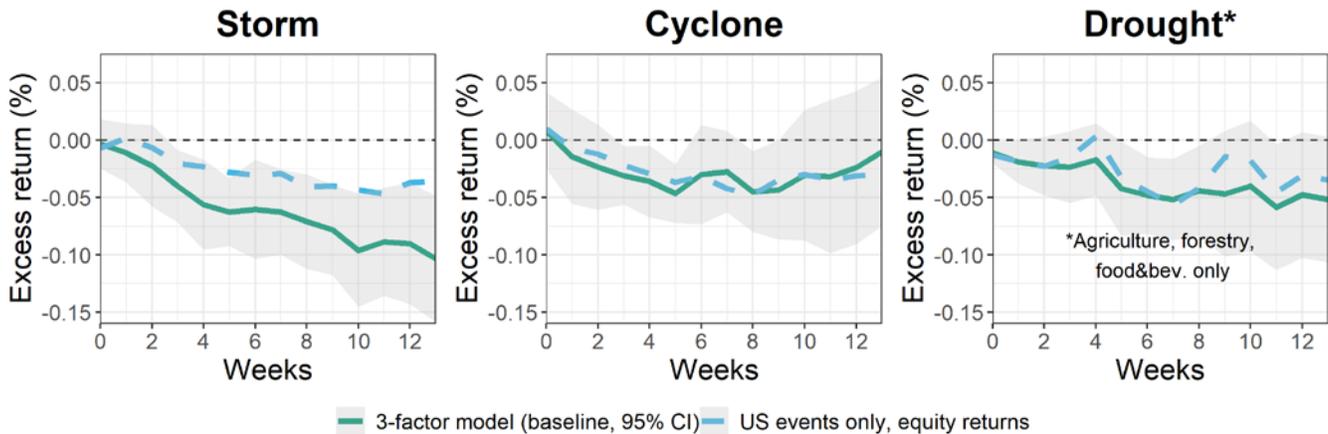


Figure 8 Cumulative effect on post-event excess equity returns (per 1% of facilities impacted), U.S. firm-event pairs only.



### 4.2 Model for Expected Returns

We strive to ensure that our conclusions are not sensitive to how we model excess returns. The baseline specification employs excess returns constructed using the Fama and French (1996) three-factor model that includes market factor, size factor, and the book-to-market factor. As an alternative, we also consider the Fama and French (1992) two-factor model, excluding the book-to-market factor, as well as the Carhart (1997) four-factor model, adding the momentum factor to the lists. We also conduct the same analysis using raw asset returns instead of excess returns.

Figures 9 and 10 compare these checks to the results of Section 3 and confirm that our conclusions are not substantially affected by common drivers of returns. Note, the large difference between factor-model and raw-returns results for cyclones. Our analysis suggests that the difference is caused by Hurricane Ike in September 2008, which also marked the beginning of the Global Financial

Crisis, and a prolonged period of poor performance for many firms. The use of a factor model, however, largely eliminates the effect of this confounding factor. This example illustrates why the use of a firm-level factor model is preferable.

Figure 9 Cumulative effect on post-event excess asset returns (per 1% of facilities impacted), robustness to modeling expected returns.

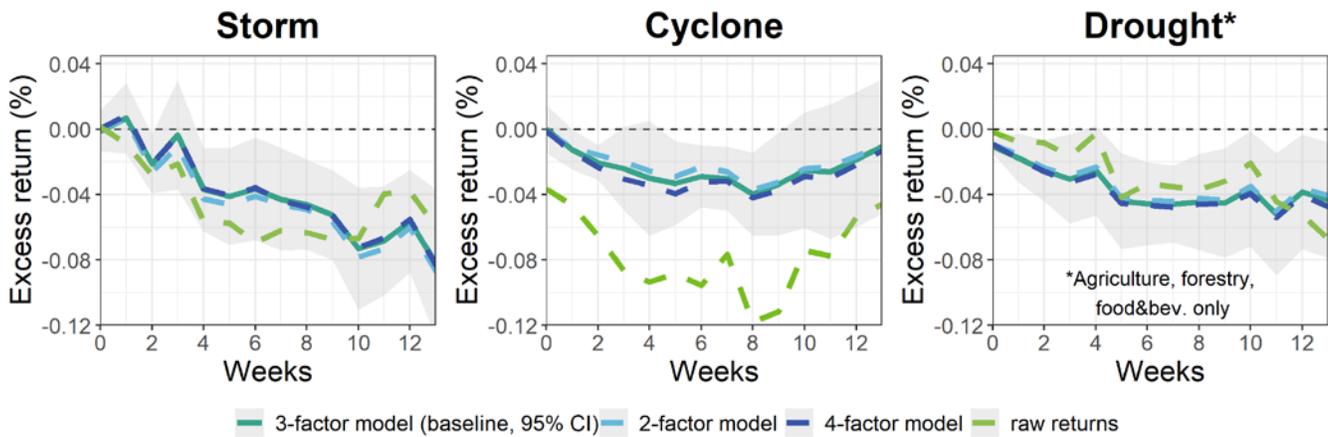
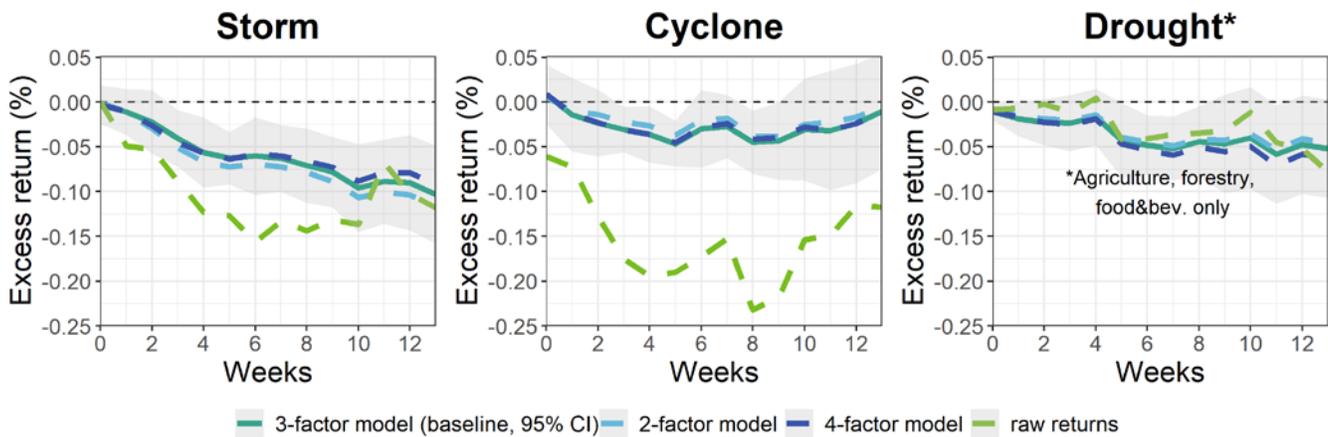


Figure 10 Cumulative effect on post-event excess equity returns (per 1% of facilities impacted), robustness to modeling expected returns.



### 4.3 Longer Horizons

How persistent is the impact of hazard events on excess returns? To answer this question, we estimate impacts at a 26-week horizon (approximately six months). Figures 11 and 12 illustrate excess equity and asset return dynamics at this longer horizon. For storms and droughts, we do not find strong evidence of reversal in valuation over time. The impact of cyclones, on the other hand, is not only smaller at shorter horizons but also disappears at a six-month horizon. We conjecture this impact difference may be due to seasonal tropical cyclones being inherently more predictable and, as a result, easier to plan and insure against.<sup>16</sup>

<sup>16</sup> See, for instance, von Peter et al. (2012), whose analysis suggests that economic losses associated with natural hazard events are primarily driven by uninsured losses.

Figure 11 Cumulative effect on post-event excess asset returns at horizons up to 26 weeks (per 1% of facilities impacted).

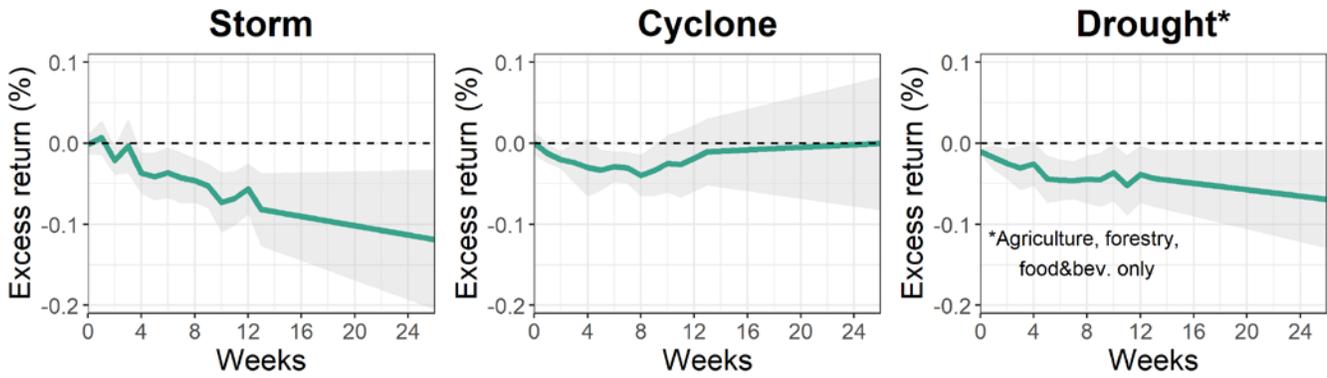
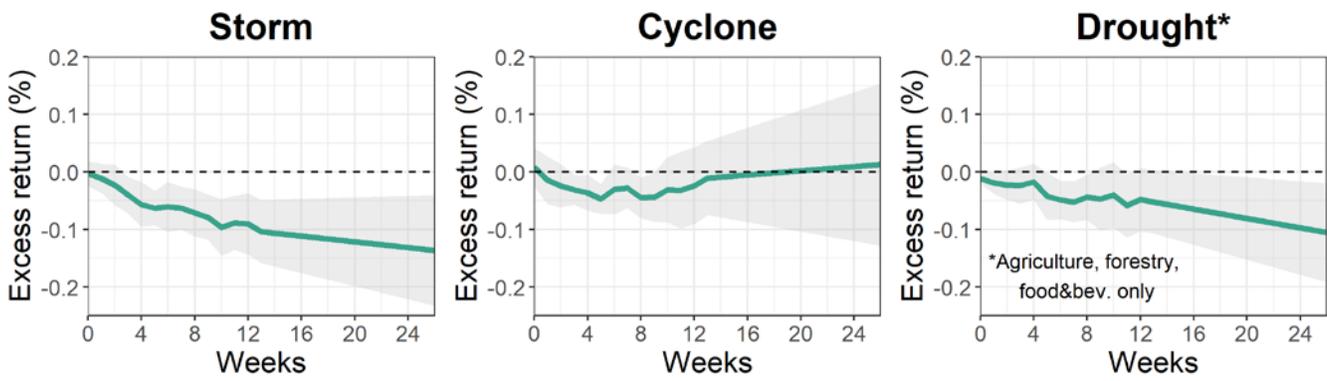


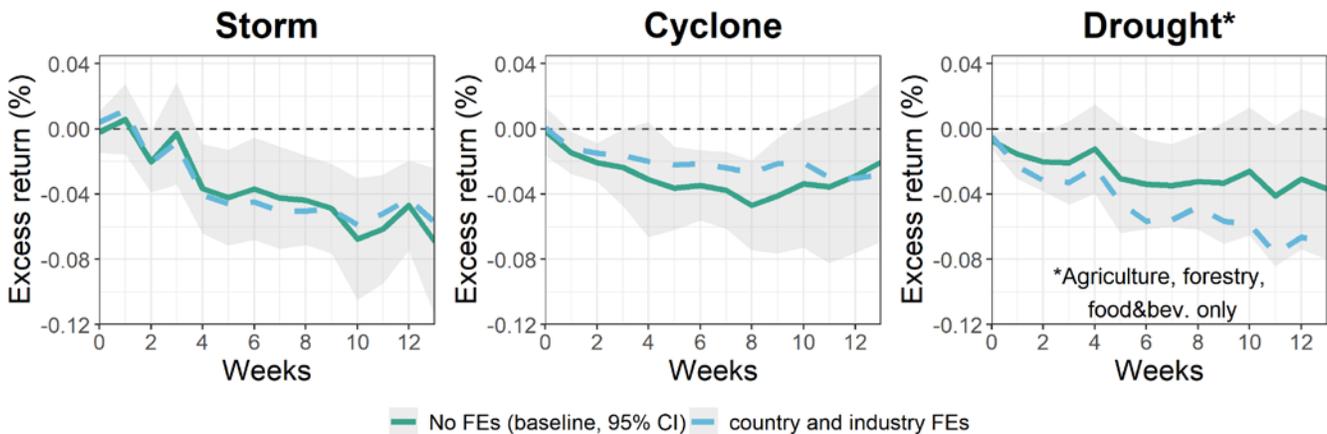
Figure 12 Cumulative effect on post-event excess equity returns at horizons up to 26 weeks (per 1% of facilities impacted).



#### 4.4 Country and Industry Fixed Effects

Finally, we confirm that the results are not driven by systematic differences across hazard event countries and industries. Figure 13 compares the baseline specification with the alternative that controls for country and industry fixed effects (FEs). Results are remarkably similar to the baseline.

Figure 13 Cumulative effect on post-event excess asset returns (per 1% of facilities impacted), country and industry fixed effects.



## 5. Benchmarking to Literature

How do our estimates of hazard event impacts on firm valuation compare to existing studies? Table 3 provides an overview of select, related studies and illustrates that the magnitudes of our estimates are broadly in-line with the literature. There are several points worth noting in comparison. First, most studies use binary classification, labeling firms as either impacted or unimpacted by an event based on certain criteria. Instead, the unique facility location data of our study allows us to proxy the magnitude of exposure of impacted firms. To make our estimates comparable to other studies, we report excess return impact at 25% of facilities exposed. Second, although data sources vary across studies, they should be comparable. For instance, the most commonly used source of U.S. cyclones data is the NOAA, which is one of the ultimate inputs for the Four Twenty Seven database. Finally, our impact estimates are conservative relative to other studies, likely because our sample skews toward the largest public firms globally, as discussed earlier.

**Table 3** Comparison of Our Results to the Literature — Impacts on Excess Equity Returns

| STUDY                       | POINT ESTIMATE | HORIZON, WEEKS | EVENTS                                     | PERIOD      | DEPENDENT VARIABLE                                | HAZARD DATA                  | FIRM DATA                               | FIRMS EXPOSURE DEFINITION                              |
|-----------------------------|----------------|----------------|--|-------------|---|------------------------------|---|--|
| Barrot and Sauvagnat (2016) | -2.50%         |                | U.S., 41 major events, mostly hurricanes   | 1978 - 2013 |   | SHELDUS                      | Compustat                               | HQ in the event county. >\$1b events (2013 USD)        |
| Our study: cyclones         | -1.09%         | 9              | Global, top-10 cyclones                    | 1999 - 2019 | Excess equity returns, Fama-French 3-factor model | Four Twenty Seven and EM-DAT | Moody's Analytics and Four Twenty Seven | 25% of facilities in the event area                    |
| Our study: storms           | -1.96%         |                | Global, top-10 other storms                |             |   |                              |   |  |
| Dessaint and Matray (2017)  | -1.03%         | 2              | U.S., top-15 U.S. cyclones                 | 1989 - 2008 | Excess equity returns relative to the market      | SHELDUS                      | Compustat                               | HQ in the event area. >\$5b events (2010 USD)          |
| Our study: cyclones         | -0.59%         |                | Global, top-10 cyclones                    | 2000 - 2018 | Excess equity returns, Fama-French 3-factor model | Four Twenty Seven and EM-DAT | Moody's Analytics and Four Twenty Seven | 25% of facilities in the event area                    |
| Kruttl et al. (2020)        | -1.59%         | 12             | U.S., cyclones                             | 2002 - 2007 | Excess equity returns, Fama-French 5-factor model | NOAA                         | CRSP-Compustat and NETS                 | >25% of facilities within 150 miles of the cyclone eye |
| Our study: cyclones         | -0.59%         |                | Global, top-10 cyclones                    | 2000 - 2018 | Excess equity returns, Fama-French 3-factor model | Four Twenty Seven and EM-DAT | Moody's Analytics and Four Twenty Seven | 25% of facilities in the event area                    |
| Seetharam (2017)            | -1.42%         | 8              | U.S. events, mostly cyclones and tornadoes | 1980 - 2014 | Equity returns                                    | NOAA                         | CRSP-Compustat and Orbis                | HQ or subsidiaries in the event state                  |
| Our study: cyclones         | -1.12%         |                | Global, top-10 cyclones                    | 2000 - 2018 | Excess equity returns, Fama-French 3-factor model | Four Twenty Seven and EM-DAT | Moody's Analytics and Four Twenty Seven | 25% of facilities in the event area                    |
| Lanfer et al. (2020)        | -0.64%         | 6              | U.S., cyclones                             | 1990 - 2017 | Excess equity returns, Fama-French 3-factor model | NOAA                         | CRSP                                    | All US firms, major cyclones (cat. 3 to 5)             |
| Our study: cyclones         | -0.75%         |                | Global, top-10 cyclones                    | 2000 - 2018 |   | Four Twenty Seven and EM-DAT | Moody's Analytics and Four Twenty Seven | 25% of facilities in the event area                    |

Note, for illustrative purposes, effects from our study are calculated for 25% of firm's facilities exposed to the hazard. Acronyms: SHELDUS — Spatial Hazard Events and Losses Database for the U.S.; NOAA — U.S. National Oceanic and Atmospheric Administration; NETS — National Establishment Time-Series; CRSP — Center for Research in Security Prices.

## 6. Impact on Credit Quality

This section highlights the first application of our climate-related hazard event study. We translate our estimates of asset return impacts into credit quality impacts, measured by probability of defaults.

Physical climate risk-adjusted EDF credit measures are probability of default term structures for corporates that account for the effects of physical risk under different future climate scenarios. The effects of physical risk on corporate probabilities of default are forecast by leveraging estimates of climate-driven economic damages as the world warms, and then translating these economic damages into firm asset shocks.<sup>17</sup> The parameters estimated in this study are an important component of the physical climate risk-adjusted EDF methodology, driving the relationship between climate events of a given severity and the magnitude of firm asset shocks caused by these events. We apply this methodology to a diversified portfolio consisting of all active firms covered by both Moody's Analytics and Four Twenty Seven; specifically, 2,072 firms across 53 countries with an average baseline one-year EDF of 0.553%. EDF value data is from November 2020.

Figure 14 shows the implied increases in the EDF term structure under different climate scenarios from NGFS and Bank of England (2019), relative to current baseline EDF values. There are four scenarios: two assuming proactive policy aimed at curbing CO<sub>2</sub> emissions, and two assuming no change relative to the current policies. Proactive policy scenarios imply a mean EDF value growth rate of around 10% by 2050 (at a 30-year horizon). Both early- and late-policy scenarios assume a transition consistent with the Paris Agreement, namely keeping global warming below two degrees Celsius by the end of the century. The difference is in timing: the late-policy scenario assumes a delayed policy change starting in 2030. The delay means that more aggressive actions are needed to meet the emission reduction target, which explains the higher EDF impact under this scenario.

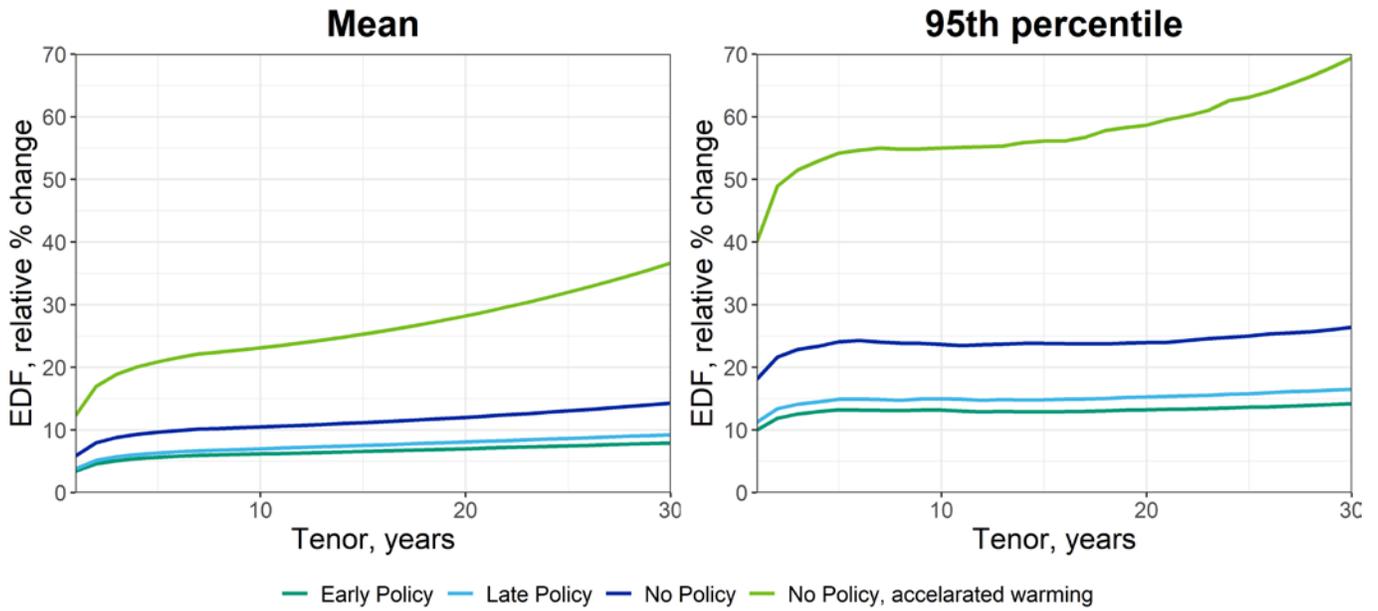
Under the no-policy scenario, projected global warming is close to four degrees Celsius by 2100. As an extreme case, we also show the shift in the probability of default term structure under the accelerated no-policy scenario proposed by Bank of England (2019), in order to cover more material late-century climate change within a 30-year scenario.

The resulting changes in credit quality are material. Under the benign proactive policy scenarios, one-year EDF values rise by around 4%, increasing further to an 8-9% increase at the 30-year tenor. But under the more severe no policy scenarios, 30-year EDF values increase by on average 14% under the baseline and 37% under the accelerated scenarios. There is also substantial heterogeneity behind the averages: EDF values increase by as much as 70% at a 30-year horizon for 95th percentile firms.

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<sup>17</sup> See Nazeran and Dwyer (2015) for a general introduction to the EDF measure. The physical climate risk-adjusted EDF metric methodology will be described in more detail in a forthcoming paper, Edwards and Mukherjee (2021).

Figure 14 Relative increase in annualized EDF term structure from baseline, portfolio of 2,072 firms.



Note, climate policy scenarios are from the Network of Central Banks and Supervisors for Greening the Financial System (NGFS) and Bank of England (2019).

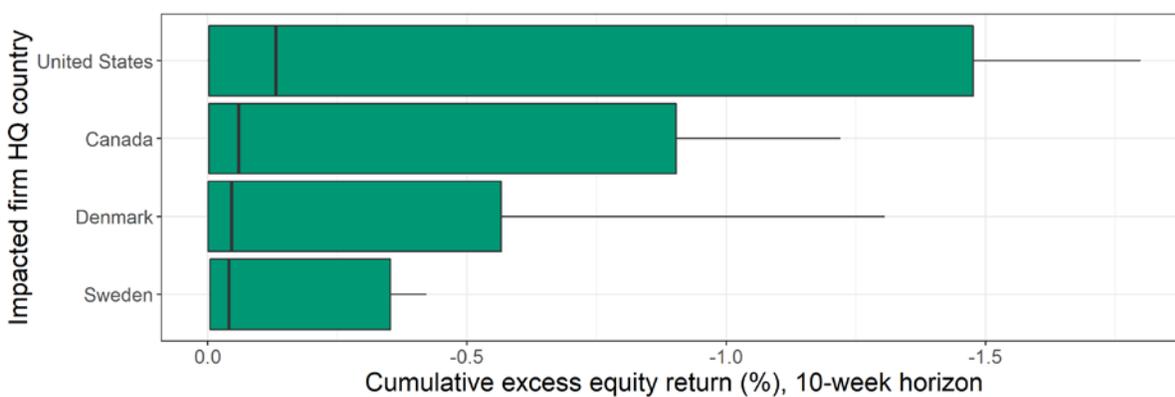
## 7. Quantification of Common Exposure to Future Climate Events Across Corporate Entities

The results of previous sections highlight economically significant impacts of climate-related hazard events on the valuation and credit quality of exposed firms. In a credit portfolio context, firms' exposures to common physical climate-related risk factors are a new source of credit concentrations, whose importance will increase with climate change and will vary with portfolio composition. In this section, we use the results of our empirical study to illustrate heterogeneous exposures to climate-related hazard events across firms from different countries, industries, and size groups.

Firms vary in their exposure to hazard event regions. For example, tropical cyclones are commonplace in the U.S. East Coast but do not occur in Sweden. As a result, Swedish firms are directly exposed to cyclones only if they have facilities in cyclone-prone locations outside of Sweden, while U.S. firms are likely to be among the most exposed. A credit portfolio concentrated in U.S. firms is thus exposed to a higher risk of losses associated with negative impacts of cyclones on firm performance.

Figure 15 illustrates cross-country differences leveraging our aggregate estimates of excess return sensitivity to hazard event exposure (Table 2). Recall, total firm-level excess return impact is a product of the share of firms' facilities impacted and the estimated excess return sensitivity. Since firms' facility exposures vary across countries, so do total return impacts. In the plot, we therefore show the product of the estimated cyclone impact (per share of facilities impacted) and the firm's share of impacted facilities. We observe intuitive patterns; for example, U.S. firms are more impacted by cyclones in general. Firms from Canada, Denmark, and Sweden — countries that are not directly affected by tropical cyclones — are nevertheless subject to downside risk due to having some facilities in cyclone-prone locations. Notably, Canada ranks second among these four countries, which is likely due to its geographical and economical proximity to the U.S.

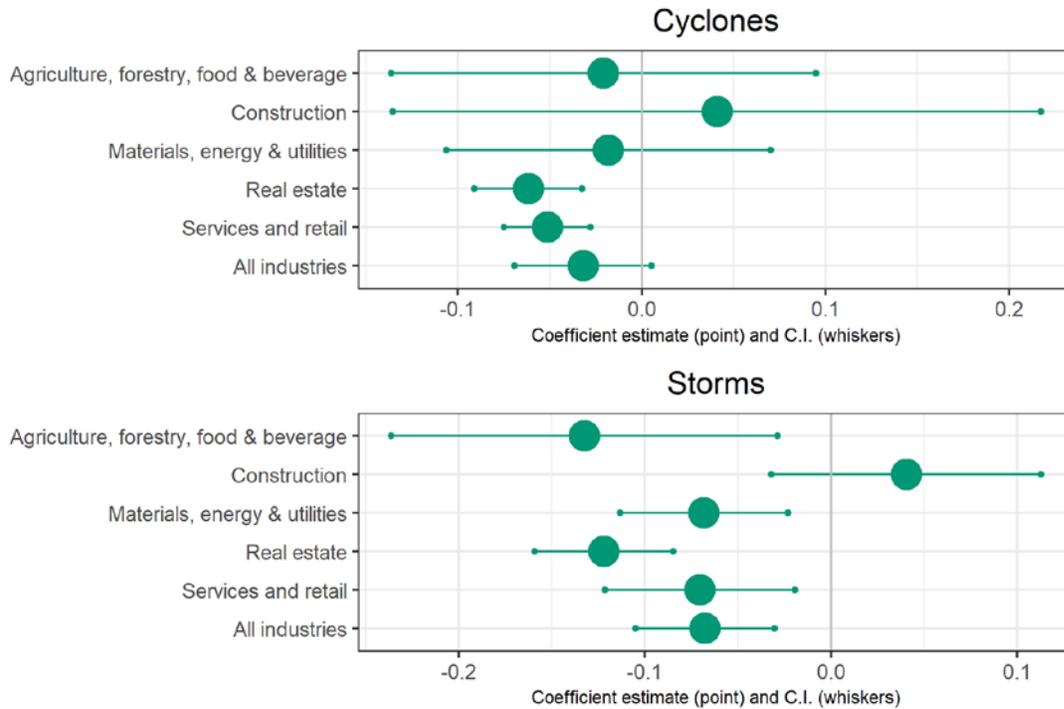
Figure 15 Differential cyclone effects across countries: excess return distributions for impacted firms.



Note, boxes show the 1st, 50th, and 99th percentiles, while whiskers show the maximum.

Effects of climate-related hazard events also vary across industries. To illustrate this, we repeat our main empirical exercise of Section 3 based on industry-level firm subsamples. Figure 16 compares the cumulative asset return impacts of cyclones and storms on six industries. For example, for storms and cyclones, the negative impact is concentrated in non-tradable industries (Real Estate and Services and Retail) consistent with these hazards having negative local demand effects. Moreover, firms do not always suffer losses due to hazard events, and few even can benefit. We observe a positive impact for Construction and Construction Materials companies after storms. This industry is expected to gain from climate hazard events, as damaged properties and infrastructures need to be replaced after cyclones and storms (see e.g., Strobl, 2011).

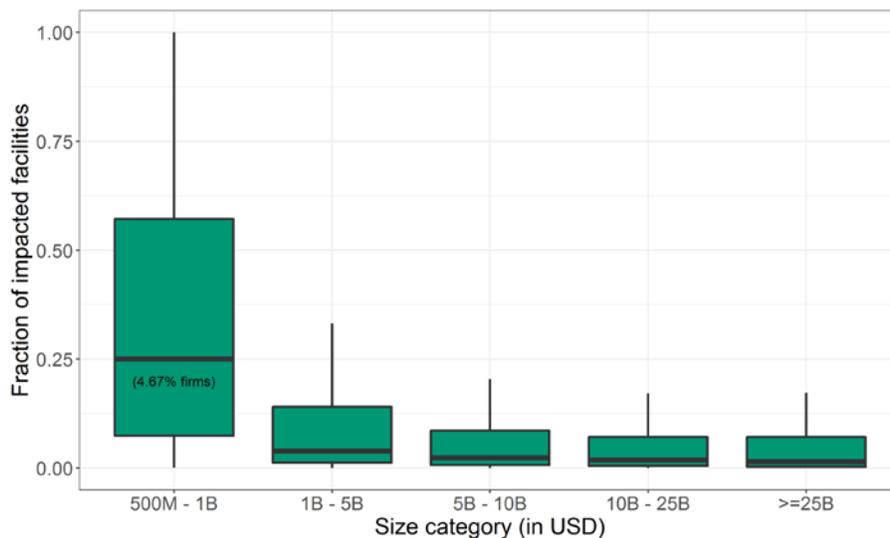
Figure 16 Cumulative effect on post-event excess asset returns at 10-week horizon (per 1% of facilities impacted), heterogeneity across sectors.



Note, solid points show the point estimate, and whiskers show a 95% confidence interval.

Finally, we observe that smaller firms are more vulnerable to climate-related hazard events. Smaller firms tend to be more geographically concentrated and hence are likely to bear significant losses once a hazard event occurs in an area of their operations. In contrast, larger firms have bigger footprints, which lower their risk exposure to local hazard events. Figure 17 illustrates differential exposure across firm sizes. Larger firms are more likely to diversify their facility locations. Therefore, the impact of a hazard event tends to be smaller. This conjecture is confirmed by studying the distribution of the fraction of affected facilities across size groups. We observe a decreasing relation between firm size and the fraction of facilities impacted. A median impacted firm in the smallest size group has around 25% of its facilities exposed, whereas in the largest size group 99% of all impacted firms have less than 20% of their facilities exposed.

Figure 17 Fraction of impacted facilities by firm size.



Note, boxes show the 2.5, 50, and 97.5<sup>th</sup> percentiles, while whiskers show 1 and 99<sup>th</sup> percentiles. Firm size is defined as sales for non-financial firms and total assets for financial firms.

## 8. Conclusion

Although there is ample literature on the effects of climate risk on excess equity returns, studies that document the impact of climate-related hazard events on corporate valuation and credit are limited. This paper is the first to quantify the relationship between corporate valuation and firm facility exposure to climate-related hazard events, as well as the first to illustrate how these exposures translate into credit quality changes. Our study has a broader firm and hazard type coverage relative to the existing literature that focuses primarily on the effects of U.S. cyclones, storms, and droughts on U.S. firms. Future research should address more hazard types, such as heatwaves and wildfires, and include analysis of smaller, private firms that might be more vulnerable to climate change.

## Appendix

Table 4 Selected Hazard Events

| HAZARD TYPE            | EVENT NAME | COUNTRY | REGION                             | YEAR | NUMBER OF IMPACTED FIRMS |
|------------------------|------------|---------|------------------------------------|------|--------------------------|
| Cyclones               | Katrina    | USA     | South                              | 2005 | 429                      |
|                        | Harvey     | USA     | South                              | 2017 | 574                      |
|                        | Maria      | USA     | Puerto Rico                        | 2017 | 113                      |
|                        | Irma       | USA     | South                              | 2017 | 879                      |
|                        | Sandy      | USA     | Northeast                          | 2012 | 1,073                    |
|                        | Ike        | USA     | South                              | 2008 | 730                      |
|                        | Ivan       | USA     | South                              | 2004 | 367                      |
|                        | Michael    | USA     | South                              | 2018 | 856                      |
|                        | Florence   | USA     | South                              | 2018 | 434                      |
|                        | Charley    | USA     | South                              | 2004 | 453                      |
| <b>Total impacted:</b> |            |         |                                    |      | <b>5,908</b>             |
| Other storms           |            | USA     | Missouri                           | 2011 | 83                       |
|                        |            | USA     | South                              | 2011 | 703                      |
|                        | Kyrill     | Germany | Nationwide                         | 2007 | 676                      |
|                        |            | USA     | South, Rockies                     | 2017 | 935                      |
|                        |            | USA     | South, Midwest                     | 2003 | 305                      |
|                        | Xynthia    | France  | Poitou-Charentes, Pays-de-la-Loire | 2010 | 97                       |
|                        |            | USA     | Midwest, Northeast                 | 2017 | 1,161                    |
|                        |            | USA     | Midwest                            | 2017 | 387                      |
|                        |            | USA     | Midwest, South                     | 2012 | 1,022                    |
|                        |            | USA     | South                              | 2003 | 319                      |
| <b>Total impacted:</b> |            |         |                                    |      | <b>5,688</b>             |
| Droughts               |            | USA     | Midwest, Rockies, West, South      | 2012 | 1,196                    |
|                        |            | USA     | Midwest, Rockies, West             | 2017 | 949                      |
|                        |            | USA     | South, Rockies                     | 2011 | 888                      |
|                        |            | VNM     | Mekong Delta, South, Central       | 2015 | 247                      |
|                        |            | ARG     | Pampas                             | 2018 | 21                       |
|                        |            | USA     | Nationwide                         | 2018 | 1,332                    |
|                        |            | ITA     | Nationwide                         | 2017 | 311                      |
|                        |            | BRA     | Northeast                          | 2014 | 163                      |
|                        |            | ZAF     | Cape Provinces                     | 2017 | 81                       |
|                        |            | AUS     | East                               | 2018 | 90                       |
| <b>Total impacted:</b> |            |         |                                    |      | <b>5,278</b>             |

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