Local Ownership and Price Discovery around Extreme Weather Events

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Abstract

In this event study, we exploit Geographic Information Systems (GIS) to show that local institutional ownership mitigates the negative impact of extreme weather events on stock prices. We determine the exposure of firms to extreme weather events by overlaying the locations of production facilities with affected geographic regions. We complement the data with firms' financial information, facilities' and investors' ownership, and facility level physical risk exposure. For storms, we find a negative cumulative average risk-adjusted abnormal daily return of 99 basis points on the event date. Local institutional ownership (IO) reduces this negative surprise by 1.3% for every additional percentage point of local ownership. We base our findings on a sample of 353 unique companies, 1,438 facilities, 68 floods, and 16 storms. Our results are statistically and economically significant for investors.

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Introduction

> *"As cooperation comes under pressure, weakened economies and societies may only require the smallest shock to edge past the tipping point of resilience*" Global Risks Report 2024, World Economic Forum (WEF)

Market segmentation increases the impact of otherwise diversifiable idiosyncratic risks on investors' portfolio returns. The WEF expects extreme weather events and misinformation to be among the biggest threats to world economies (World Economic Forum, 2024). While extreme weather events already caused \$3 trillion losses from 1980, of which € 560 billion in the EU, geopolitical fragmentation increases informational barriers, thus constraining investment decisions (Pellegrino et al., 2022; BIS, 2021).[1] An increase in information barriers will accentuate market segmentation, where idiosyncratic risks, such as extreme weather events, affect investor portfolio returns through the uncertainty channel (Kruttli et al., 2023)

Information asymmetry among investors introduces investment uncertainty, thus challenging the assumption of market efficiency. Some models relaxed the assumption of market efficiency to investigate deviations from mean-variance-efficient portfolios. Merton (1987) assumed that the knowledge of investors about stocks is homogeneous over the assets they know, but they might not know all the assets. Klein and Bawa (1977) assumed that the depth of knowledge of investors about stocks is heterogeneously distributed.

To reduce uncertainty, investors focus on stocks they know better, where knowledge is proxied by means of geographical proximity in the literature. Coval and Moskowitz (2001, 1999) show that investors earn positive abnormal returns by investing in assets that are geographically closer to them. Van Nieuwerburgh and Veldkamp (2009) develop a model in which investors focus on geographically closer stocks due to a comparative advantage, thus neglecting others for the same reason.

Extreme weather events increase the uncertainty on stocks performance, thus impacting investors' portfolios under market segmentation. Kruttli et al. (2023) developed and empirically tested a model that shows how uncertainty related to extreme weather events affects the performance of under-diversified investor portfolios. Alok et al. (2020) finds that deviations from market efficiency

[1] Source: Economic losses from climate-related extremes in Europe (8th EAP), EEA, 21 April 2023.

during extreme weather events are more related to behavioural biases, such as the salience of these events, than to superior information on stock performance.

In this paper, we address a research gap in the interaction between uncertainty, market segmentation, and stock prices. Consequently, in the spirit of Coval and Moskowitz (2001), we investigate whether local institutional ownership decreases the negative impact that uncertainty has on stock prices during extreme weather events. To this extent, we analyse the price discovery process of publicly listed companies with heterogeneous stakes of local investors' ownership by using a convenient identification strategy provided by the occurrence of extreme weather events. We then test two different mechanisms to show that local investors have more knowledge about companies' exposure to extreme weather events. First, companies with a higher expected annual loss to a specific extreme weather event and higher local institutional ownership should show a lower negative surprise from the event. Second, the greater the distance between the impacted facility and the company headquarters, the weaker the informational advantage of local institutional investors.

Market segmentation is both a consequence and a cause of uncertainty due to information asymmetry. On the one hand, this is the consequence of increased investment uncertainty due to information asymmetry, but it can lead to positive deviations from the benchmark (Van Nieuwerburgh and Veldkamp, 2009; Coval and Moskowitz, 2001, 1999). On the other hand, it increases the uncertainty of stocks when local shocks occur, increasing thus the probability of a negative portfolio performance due to portfolio underdiversification (Kruttli et al., 2023). In our analysis, we assume that foreign investors do not access the same type of information as local ones, commonly defined as the "*information assumption*". This happens for several reasons: investors might have a comparative advantage over their local stocks and actively ignore signals from others (Klein and Bawa, 1977), the entry cost to access is too high, or they simply ignore their existence (Pellegrino et al., 2022; Merton, 1987). We expect this assumption to hold also for extreme weather events, which are a yet-underinvestigated risk for investors.

To answer the research question, we focus on Europe, a region that was historically exposed to market segmentation and increasingly affected by extreme weather events (Boermans and Galema, 2023).[2] To this extent, we use data and methodologies provided by European institutions (ECB,

[2] For more information on the impact of climate change in Europe, look at Fragile State Index (FSI) and (Kemp et al.,

2023; EIOPA, 2022). We identify companies impacted by extreme weather events by overlaying the area of the events with the location of the facilities provided by the E-PRTR.[3] We record the area, event time and intensity of floods from the Dartmouth Flood Observatory (DFO) (Brakenridge, 2021), while for winter windstorms from the *"Climate Data Store"* of the European Commission. We implement a name matching algorithm to link the ownership names of the E-PRTR facilities with the ownership structures of the companies, thus linking the facilities with the closest publicly listed company in the ownership structure. We then use FactSet to calculate the cumulative abnormal returns (CAR) adjusted for the risk of the securities during the event.

Due to the innovative data sources and geographical focus we first validate our approach with a case study analysis and apply the event study methodology to the entire sample. We provide a case study analysis for the winter windstorm Ciara in February 2020 and the July 2021 river floods in Germany, Belgium, and the Netherlands.[4] We implement a typical event study approach for all events from 2014 to 2022 following guidelines developed in the literature (Barnett, 2023; Barrot and Sauvagnat, 2016; MacKinlay, 1997). To compute abnormal returns, we use the most established factor models (Fama and French, 1993; Carhart, 1997; Fama and French, 2015) and test for significant differences from actual returns using the robust cross-sectional variance adapted to account for event-induced variance (Boehmer et al., 1991). We then test for the impact of local ownership on CAR in a panel regression setting.

We have four key results: (i) in line with the literature, we find that winter windstorms trigger a cumulative average risk-adjusted negative investor reaction of up to one percentage point at the event date (Kruttli et al., 2023; Huynh and Xia, 2021; Alok et al., 2020). Winter storms have a longer forecast horizon and higher forecast uncertainty compared to floods, triggering a stronger reaction (Merz et al., 2021). In addition, investors are less reactive to flood risks (Giglio et al., 2023; Alok et al., 2020). (ii) A higher local institutional ownership reduces the negative impact of windstorms by 1.3% percent for every percentage point. This result is economically and statistically significant

2022).

[3] An overlay is a procedure that estimates the attributes of one or more features by superimposing them over other features and figuring out the extent to which they overlap. You use overlays to estimate the attributes of features in a map layer based on data in another map layer. We follow this practice, commonly referred to as *"spatial finance"*, which has significant potential to help improve transparency and accountability (McCarten et al., 2021; Patterson et al., 2022).

[4] The case study for winter wind storms was selected by the European Insurance and Occupational Pensions Authority (EIOPA), based on its impact. For floods, we analyse the July 2021 summer floods, which caused approximately € 50 billion economic damage, as reported in the 8th EAP.

and in line with the "information hypothesis" (Giannetti and Laeven, 2016; Van Nieuwerburgh and Veldkamp, 2009; Coval and Moskowitz, 2001). (iii) Where local institutional ownership interacted with companies' exposure to windstorms, expressed as the Expected Annual Loss (EAL), mitigates the negative investor reaction after the event. (iv) When local institutional ownership is interacted with the distance of companies' headquarters from the affected, then the negative investor reaction after the event is exacerbated. The price discovery after shocks is in line with the information hypothesis that the response should be less strong for local investors, who already priced in the risks or stronger with a greater informational distance.

We face two main challenges in implementing the empirical setting of our event study: limited access to information on firm physical assets, difficulty translating economic losses into financial losses, price shocks, and a limited sample size of time series (Bressan et al., 2022; Alekseev et al., 2021). To overcome the first challenge, we use the E-PRTR register to identify the location of production facilities. We then ensure that we only keep stocks with a price above € 5 during the estimation period and with at least 10% free float, a common practice in other studies (Barnett, 2023). To overcome the second challenge, we estimate the counterfactual during the event window using a fixed 90-day estimation window of daily returns free of weather-related disaster events for every company and every event. In doing so, we are close to the 120-day estimation period implemented by Kruttli et al. (2023) and more conservative than Blanco et al. (2024).

Our work adds information on investors' views related to climate risks, thus contributing to current interests in climate finance (Starks, 2023). In particular, we contribute to two main streams of literature. First, we contribute to the literature that analysing the impact of securities' ownership on investors' reaction to shocks. For example, Huynh and Xia (2021) show that investors overreact by depressing prices after natural disasters, resulting in higher future expected returns for the impacted securities. Blanco et al. (2024) show that institutional investors with a relatively high portfolio exposure to natural disasters divest from disaster-hit stocks, decrease the trading intensity in non-hit stocks, and their trading decisions predict low medium-term returns. Furthermore, Glossner et al. (2024) investigate how the ownership of securities affects price pressures after the Covid-19 pandemic. We add to this literature by investigating the role of local institutional ownership in mitigating the negative impact of extreme weather events on stock prices. We investigated two potential mechanisms: the distance between facilities and headquarters and the exposure to expected annual losses from extreme weather events. We provide an empirical contribution to this literature by exploring how local informational advantages shape uncertainty driven by extreme weather events.

Second, we contribute to the literature analysing the impact of extreme weather events on asset prices using innovative data sources (Kruttli et al., 2023; Blanco et al., 2024; Huynh and Xia, 2021; Alok et al., 2020; Bressan et al., 2022). In the specific we exploit product release and transfer registers in Europe to identify impacted facilities. This work adds to the debate that climate data should be publicly available for replicability and transparency in climate finance (Condon, 2023). The use of non-financial data for financial analysis has proven to be successful in reducing the return gap between quantitative asset managers and those who rely on traditional asset picking skills in the financial sector, such as industry knowledge (Bonelli and Foucault, 2023). Furthermore, the abundance of alternative data sources reduces the advantages of active asset managers (Dugast and Foucault, 2023). We use the European Pollutant Release and Transfer Register (E-PRTR) to identify the location of production facilities in Europe, measure their exposure to extreme weather events, and analyse investors' reaction to extreme weather events. In doing so, we build on recent work with the E-PRTR to analyse emissions data (Germeshausen and von Graevenitz, 2022).

We trust that our work is also relevant to European institutions and finance practitioners. For example, we believe that the E-PRTR needs more information on the facilities' workforce, as well as their financial value and the current level of adaptation measures. This would ensure a more precise damage estimate and a more in-depth financial analysis. In terms of weather-related disasters provided by Copernicus, they show good and precise geographic coverage; however, storms with lower wind intensity for 2018 and 2019 are missing, and no data for tropical Mediterranean storms are provided, an issue that gained in importance after the sinking of the “Baysian" in the Mediterranean see. For practitioners, we show the usefulness of developing alternative data measurements independent of ESG rating providers that can also be used for research in the context of biodiversity (Condon, 2023).

We structure the paper in the following way. In Section I, we introduce the theory motivating our empirical analysis, and in Section II, we formulate our research hypotheses. We then introduce the empirical setting in Section III. In the following Section IV, we introduce the sample. We then provide our results to the hypotheses formulated in Section V. Finally, we develop our conclusion in

Section VI.

I Informational barriers, uncertainty, and security prices

International asset allocation is less efficient than theory predicts due to frictions that make access to information more costly for investors. In a model developed by Pellegrino et al. (2022), the representative investor z is endowed with a prior distribution of information to form expectations based on freely accessible information and additional costly signals. Costly signals are modelled to negatively impact the utility function of the representative investor z. Investors form expectations based on both costly and free signals. The higher the difference in expected returns that is driven by costly signals, the more negative the impact on the utility function of the investor.

Share demand is more elastic to net returns when investors have more precise information on the securities. Investors dislike costly signals and will only purchase them if they expect this additional information to considerably improve their information quality (Pellegrino et al., 2022). Since investors experience a loss of utility in acquiring costly information, their asset allocation is biased. In other words, the easier it is to acquire information, the more elastic the shares are to net returns, and capital is only allocated where investors achieve the highest net returns. Consequently, the higher the informational distance, the lower the share elasticity to price changes.

The preference of investors to invest "closer" is related to cultural, geographical, and linguistic proximity between countries (Pellegrino et al., 2022). From an investor's perspective, a higher difference in opinions among investors is a source of uncertainty, which even in small amounts can lead to significant differences in long-term beliefs of agents (Acemoglu et al., 2016). In Europe, investors reserve a different treatment for equally risky investments, as far as climate risk is concerned, depending on whether investments are in the home country or abroad (Boermans and Galema, 2023). In addition, investors achieve higher returns when they invest locally (Giannetti and Laeven, 2016; Van Nieuwerburgh and Veldkamp, 2009; Coval and Moskowitz, 2001, 1999).

Market segmentation leads to an underdiversified portfolio allocation, which exacerbates the impact of idiosyncratic shocks. Merton (1987) argue that investors only invest in securities they know about, leading to an underdiversified portfolio allocation where even shocks to idiosyncratic volatility have an impact on expected returns. In a standard CAPM world, idiosyncratic and local extreme weather events are diversified and do not affect the discount rate of the representative investor (Strobl, 2011). Kruttli et al. (2023) developed a model to explain how uncertainty related to extreme weather events impacts investors' and firms' returns in segmented markets.

Extreme weather events impact company returns and volatility through dynamic probabilities. Kruttli et al. (2023) show that uncertainty related to extreme weather events affects asset prices in segmented markets. Specifically, the mechanism occurs through two uncertainties impacting cash flows: the physical probability of an event hitting a company and the uncertainty about the real extent of the damage once the company is hit. In their model, the authors define $\sigma^2_{g,i}\phi$ as the uncertainty of the expected impact conditional on the company being hit by the disaster and $\mu^2_{g,i}\phi(1-\phi)$ as the variance driven by the probability of the company being impacted by the disasters. Both components depend on ϕ, which is the probability that a firm will be hit by a weather-related disaster. Consequently, $\mu^2_{g,i}\phi(1-\phi)$ is positive only if a company is not hit by an event as long as the event lasts, while $\sigma^2_{g,i}\phi$ is positive also after the event hits the company.

Uncertainty from extreme weather events has a negative impact on the materially exposed securities' prices, under higher levels of market segmentation. Kruttli et al. (2023) link investors' knowledge about firm i with the uncertainty of weather-related disasters and the value of the firm. Uncertainty related to disasters negatively impacts the value of the company if it exceeds positive impacts and is exacerbated if the share of wealth of investors who know about the company i is low. In other words, the less investors know about firm *i* and its vulnerability to expected annual losses, the more prices will turn negative. Kruttli et al. (2023) show that many companies experience negative cumulative abnormal returns in the short term. Specifically, more than 50% of the impacted firms experience negative cumulative abnormal returns (CAR) even up to 120 days after the inception of the hurricane compared to their non-impacted peers.

II Hypotheses

From the theory introduced in Section (I), we know that investors exhibit biased investment behaviour, which is impacting asset prices during and after extreme weather events. To empirically test the theories introduced we formulate four hypotheses.

Incidence uncertainty impacts asset prices before extreme weather events impact a region. From

Section (I), we know that the probability of occurrence has a negative impact on asset prices. From the literature, we know that the uncertainty of damage and occurrence is greater for windstorms compared to floods (Merz et al., 2020). We included a practical example of early warning systems for floods and storms in Appendix (A). For Storm Kyrill in Australia in January 2024 we show that the incidence precision increases over few days. Additionally, for the floods in Germany in June 2024 we show that prediction's certainty is higher. Now given that the firms' in the sample we analyse are materially exposed to physical risk for industry belonging we hypothesize that:

H_1: *"Securities of Companies impacted by winter wind storms experience more negative cumulative average abnormal returns (CAAR) than those impacted by floods."*

In Section (I) we learnt that local investors have an informational advantage compared to other investors when signals are costly; as such, we expect companies for which institutional investors have, on average, a higher preference for local investments to experience a lower negative surprise from extreme weather events. This is a plausible expectation because, on the one hand, investors do more due diligence on local companies reducing the information distance (Van Nieuwerburgh and Veldkamp, 2009; Coval and Moskowitz, 2001, 1999); On the other hand, the share elasticity is higher for local investments and are more likely to demand a higher quantity than foreign investors for a lower price change if they expect higher returns, thus mitigating the negative impact on prices (Pellegrino et al., 2022). Consequently, demand will adjust faster to an increase in supply compared to companies whose shares are more held by foreign investors. From this follows the second hypothesis:

H_2: *"The higher the degree of local institutional ownership in a security before an event, the higher CAR at and after event occurrence."*

We test the link between investors' informational distance and securities' performance over two possible channels: the first one tests the ability of local investors to precisely assess securities exposure to local extreme weather risks; the second one analyses how the geographical distance of the impacted facility from the headquarters influences investors' reaction. For the first channel, we expect local investors to have deeper knowledge of the company's exposure to extreme weather events. In other words, interacting local ownership with expected annual losses from extreme weather events positively impacts securities' performance at the event date. Consequently, to test the first channel, we formulate the third hypothesis as follows:

H_3: *"The positive impact of local security ownership is higher when the affected facilities are located in regions with greater exposure to extreme weather events."*

In the Introduction and Section (I) we learn that investors have lower information precision the higher the information distance. Consequently, whenever a facility is located further away from the company's headquarters, the lower the investors' knowledge of the impacted physical assets. As such, the higher the distance between firms' facilities and firms' headquarters, the lower the positive impact of local ownership on securities performance. Intuitively, companies rarely disclosed their exposure to extreme weather events at a facility level, thus accessing this information will cost more to investors. We test the second channel by formulating the fourth hypothesis as follows.

H_4: *" The positive impact of local security ownership will become weaker the higher the distance between a facility and the companies' headquarters".*

III The empirical setting and physical risk scores

To answer the research question, we linked facility owners with the company ownership structure, analysed the landscape of security owners, extracted geographical information on the occurrence of events, and used this information to investigate the impact of events on securities' prices and investors' behaviour. In the following section, we explain the most relevant steps needed to finalise the sample and perform the analysis such as: the algorithm to link facilities with listed companies, the calculation of companies' Expected Annual Losses (EAL) from extreme weather events, introduce the implemented event study methodology, and explain how we define local institutional ownership.

III.a The name matching algorithm: linking securities with facilities

We link facility owners with securities by matching companies' names with a name matching algorithm. To this extent, we extend the methodology developed by Michel Nijhuis by first computing several string similarity measures and then using testing several machine learning algorithms to combine the measures' strengths in the name matching outcome.[5]

To simplify the matching procedure, we preprocess the company names from the sample of facility owners and the sample of company names. We normalise company names with the following

[5] Company Name Matching by Michiel Nijhuis; DNB Data Science Hub; Medium

steps. First, we convert characters into lowercase. Second, we construct a comprehensive list that includes all frequently occurring suffixes across European languages. For example, we abbreviate “International" to “#INT" thus reducing computational complexity. Third, we compute the cosine similarity string measure to identify and retain strings that exhibit a similarity above a 60% threshold.

After the preprocessing stage, we compute string similarity measures with complementary strengths on the name matching combinations that are retained after computing the cosine similarity. In this stage, we compute the Jaro-Winkler, Levenshtein, and Q-gram similarity between every retained name matching combination of the facility owners' names sample and the company names sample. These three measures are complementary. For example, the Jaro-Winkler measure focuses on prefix similarity, the Levenshtein measure on the edit distance between two strings, and the Q-gram is effective at identifying localized differences (van der Loo, 2014). Additionally, while character-based measures like Levenshtein and Jaro-Winkler perform well with typographical errors, they struggle to accurately capture the similarity between strings when there are changes in the order of the characters. These changes are captured by the Q-gram measure (Gali et al., 2019).

In the next step, we use different machine learning classification algorithms with the string similarity measures as input variables and test their classification quality on a manually classified sample. To merge facility owners with company names, we create a randomly collected and balanced sample of 2,400 entries that we manually classify to assess the performance of several machine learning (ML) algorithms in combining string similarity measures to match company names. To avoid overfitting, we split the sample into training and test sets using cross-validation. The results of this exercise are provided in Table (I).

We decide to use the Gradient Boost method to classify the matches. We assess which supervised machine learning algorithm performs best based on a set of performance measures. For cross-validation of the test and training samples, we split the sample into six and test the algorithm quality on the left-out test sample. The procedure is repeated until we compute the accuracy, the F1 score, precision, and recall in all test samples for all the methods compared. In Table (I) we see that the gradient-boosting classification method shows the highest accuracy ratio and very high levels of precision and recall and a rate of 87% of true positives. We also base our decision on an Area Under the Curve (AUC) analysis, which we provide in Appendix (**??**).

		Linear SVM	Logit	Random Tree	Naive Bayes	Ada-Boost	Gradient-Boost	Random Forest	Extra Tree	KNN
Accuracy	μ	57	72	85	69	81	86	86	86	82
	σ	7	11	4	6	8	5	4	5	5
F1	μ	37	71	84	74	79	85	86	85	81
	σ	37	16	5	7	12	6	5	6	7
Precision	μ	29	68	86	63	83	87	88	88	81
	σ	29	8	2	4	2	4	3	3	2
Recall	μ	50	78	83	90	78	84	83	83	82
	σ	50	24	7	13	18	8	7	8	11

Table I. Supervised machine learning algorithms by classification performance: Table (I) reports the Accuracy ratio, F1 ratio, Precision, and Recall for all classification models tested to merge company names over the cross-validation samples. The methods presented include the linear support vector machine (SVM), logistic regression (logit), random forest (tree), Naive Bayes, AdaBoost, Gradient Boost, Random Forest (RF), Extra Tree (E.Tree), and k-nearest neighbor (KNN) classification models. μ and σ denote the average and standard deviation of algorithm performance across all cross-validation samples. The accuracy ratio is defined as $AR = \frac{a_R}{a_P}$, where a_R is the area under the performance curve of the model compared to a random classification model, and a_P is the area under the perfect model curve compared to the random model. *Precision* is the ratio of true positives to all observations classified as positive, while *Recall* is the ratio of true positives to all observations that should have been classified as positive. The harmonic mean of accuracy and precision is denoted by the *F1* ratio.

After running the gradient boost method on the full sample of potential matches, we link facilities with the first publicly listed entity in the ownership structure of the company. To this extent, we identify the first publicly listed company in the historical ownership chain of the facility owner. Amadeus provides information on subsidiaries, immediate shareholders (ISH), domestic ultimate owners (DUO), and global ultimate owners (GUO) for each company and year. We link only those companies that have a 50% ownership structure in linked companies in the ownership chain. To select which stock is linked with the facility, we first take the subsidiary, then the owner of the subsidiary, and then ISH, DUO, and GUO.

III.b Expected annual losses (EAL): The ESCB Methodology

To compute physical risk indicators at a company level, we leverage on the framework developed by the Eurosystem of Central Banks (ESCB) (ECB, 2023). This approach has several advantages. First, we calculate indicators using facility information and aggregate them on a company level. Second, we do not need to rely on the methodology of a third-party provider that might change or become unavailable over time (Condon, 2023). Third, our results can be replicated by other researchers.

We measure risk exposure by combining information on the location of the facility, extreme weather events, land use, building-type distribution maps, and damage functions. We use location data on facilities provided by the E-PRTR. Copernicus Land Monitoring provides land use maps, while Delft University offers access to flood hazard maps with intensity and return periods (Paprotny et al., 2019, 2017). Similarly, we use historical footprints of European winter wind storms since 1980 and computed return periods for every pixel assuming Gumbel distributions, a common practice in actuarial sciences (Kiyani et al., 2021). We then derive damage functions for floods as described in Huizinga et al. (2017), while for windstorms we use damage functions calibrated in Europe for different types of buildings following Feuerstein et al. (2011). We derive the distribution of building types by country from Jaiswal et al. (2010).

To calculate expected annual losses (EAL), we follow the method suggested in Antofie et al. (2020). Specifically, given the probability of an event exceeding an intensity threshold, for instance, a wind speed between 30 km/h and 35 km/h for wind storms, and the damage ratio associated with this intensity range, we then calculate EAL as a weighted average over all intensity ranges and their respective probabilities. To compute the EAL we first calculate the probability of an event's occurrence as follows.

$$p_n = \frac{P_{T_n} - 1}{\prod_{i=T_1}^{T_n} (1 - p_i)} + 1 \tag{1}$$

In Equation (1), P_{T_n} represents the number of times a stochastic process exceeds some critical value, in this case related to the return period, per unit of time (e.g., the probability that wind intensity exceeds 100 km/h in the next 10 years). We define the return period as T_n, p_n as the probability of occurrence for the same return period, and p_i as the probability of occurrence for a single event. In practice, we compute the probability of occurrence for different periods as shown in the following examples. Consider the return periods T_{100}, T_{50}, T_{10}. The probability of occurrence for the longest return period (e.g., T_{100}) equals the probability of exceedance. From this we can calculate all other individual probabilities associated with the events.

$$\begin{gathered} p_{100} = P_{T_100} = \frac{1}{100} = 0.01 \\ p_{50} = \frac{P_{T_{50}} - 1}{(1 - p_{100})} + 1 = \frac{0.02 - 1}{1 - 0.01} + 1 = 0.0101 \\ p_{10} = \frac{P_{T_{10}} - 1}{(1 - p_{100})(1 - p_{50})} + 1 = \frac{0.1 - 1}{(1 - 0.01)(1 - 0.0101)} + 1 = 0.0816 \end{gathered} \tag{2}$$

In Equation (2), $j = 1$ and i change depending on the return period. For example, $p_{100,1}$ is the probability of occurrence for return periods of 100 years for one year. Consequently, assuming that the events are independent, we express EAL for all events in one year as

$$EAL = \sum_{i=T_1}^{T_n} (p_i L_i). \tag{3}$$

In Equation (3), L_i is the percentage loss for all physical assets the company has for a given hazard that occurs with a given intensity at a given location, accounting for the land use and the distribution of buildings in that area.

We compute EAL at the facility level and average them with equal weights over facilities that are linked to a publicly listed company. [6] To compute EAL by companies, we aggregate EAL from the facility level to the company level.

III.c Measuring securities' local institutional ownership

We calculate the ownership of stocks at the company level by aggregating the investments of all institutional owners (IO) in a company by country. For example, $IO1$ invests in company A and is from country A, while $IO2$ and $IO3$ invest in companies A, C and are from countries A, B, respectively. Then the stock or local equity of all IO investing in company A is given by the sum of the investments of $IO1$ and $IO2$ in A. This measure is similar to one of the measures suggested by Coval and Moskowitz (2001) and to the home bias measure of Coeurdacier and Rey (2013). Consequently, we collect all the IO investments in the companies of our sample and assign them to local or not depending on their country of residence for every company. Since IO investors are generally more informed, we believe that our result will provide a conservative lower bound estimate. We define local institutional equity ownership ($LO_{(i,t)}$) at the company level as follows:

$$LO_{(i,t)} = 1 - \left(\frac{\textit{Share of foreign institutional ownership in company i at time t}}{\textit{Share institutional ownership in company i at time t}} \right) \tag{4}$$

We use the $LO_{(i,t)}$ measure as a proxy for the general local preference level of investors in

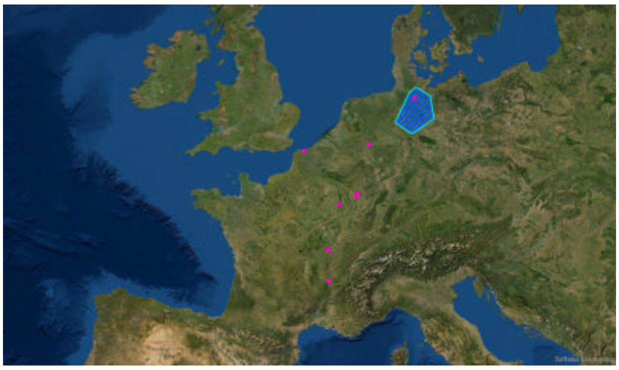
[6] Hereby we follow an approach suggested in Kruttli et al. (2023) as facility weighting did not lead to significantly different results.

company i.

III.d The event study

We follow the literature on how to implement an event study to analyse the impact of extreme weather events on securities' prices (Barrot and Sauvagnat, 2016; MacKinlay, 1997). Events of interest are major windstorms and floods that occurred in Europe since 1 January 2014 and until 31 December 2021. The time frame is set to account for increased investor attention towards climate change that led to the Paris Agreement on 12 December 2015. We set the event window to investigate securities' prices to begin five days preceding landfall for windstorms and two days before the occurrence for floods.[7] The event window ends twenty-two trading days after the beginning of the event to allow all market participants to adjust their positions.

We assign companies to events based on whether they were in a region impacted by an extreme weather event. We include publicly listed companies that owned a production facility in an impacted area at the time a major extreme weather event occurred. Figure (5) provides an example of our flood selection criteria; similar criteria apply to windstorms. Company Y, shown in Figure (1a), has an industrial site located in the area affected by the flood in July 2017 and is included in our study. Company X, in Figure (1b), does not have an industrial site in the affected area and is excluded from our sample.



(a) Company Y is included

(b) Company X is not included

Figure 1. On 25 July 2017 Company Y is included in the event study and Company X not: In Sub-Figure (1a) the pink dots indicate the location of the production facilities from Company Y. The area where a major flood occurred on 25 July 2017 is the blue shaded area that overlays one of the production facilities of company Y. In Sub-Figure (1b) the yellow dots indicate the location of the production facilities of Company X. The area where a major flood occurred on 25 July 2017 is the blue shaded area that does not overlay any of the production facilities of company X.

[7] This decision follows from other studies such as Nagar and Schoenfeld (2021) and the literature on early warning systems Merz et al. (2020)

We compute expected returns and abnormal returns using the market model and the factor models most affirmed by Fama, French, and Carhart (Fama and French, 1993; Carhart, 1997; Fama and French, 2015). [8]

We minimise bias in the estimates due to the occurrence of multiple events. First, we set the estimation window for an event to end before the occurrence of each event. Second, we retain only those securities for which the estimation window does not overlap with events of the same nature. This ensures that we isolate the idiosyncratic damage generated by specific occurrences.

We maximise the precision of the expected returns' estimates for each security, balancing a longer estimation window with a larger sample size. A typical estimation window ranges from 120 to 30 days (Kruttli et al., 2023; Blanco et al., 2024). We opt to include as many companies as possible for each event to increase the precision of the coefficients. Consequently, we choose a 90-day estimation window. In Figure (2), we summarize the relevant information on the length of the estimation and the event window.

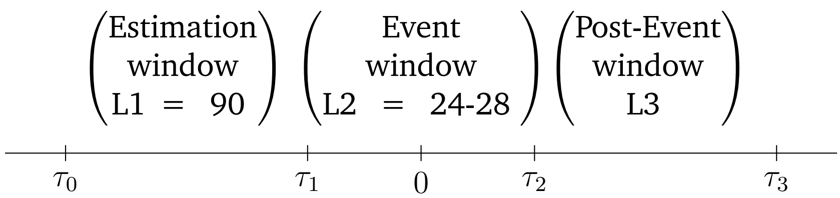


Figure 2. The windows of the event study are fixed for all events: In the figure above L_1, L_2, and L_3 are defined in days. For example, the estimation window is characterised by a period of 90 days.Where L_2 varies depending on the type of hazard (e.g. 28 for winter storms as they are highly predictable).

For the event study, we compute abnormal returns (AR), CAR, and CAAR. Abnormal returns $AR_{i,t}$ are defined as the difference between the actual and expected returns. We compute abnormal returns using various expected return models. We calculate CAAR generated by extreme weather events across multiple events and companies. Consequently, we aggregate abnormal returns first over time and then across companies.

[8] A large body of literature suggests that various factors, drawn from the Kenneth French Data Library, are important in explaining the returns on equity portfolios. Here, we use factors calibrated for European developed markets.

$$CAR_{i,t} = \sum_{t=\tau_1}^{\tau_2} AR_{i,t} \tag{5}$$

$$CAAR_t = \frac{1}{N}\sum_{i=1}^{N} CAR_{i,t}. \tag{6}$$

In Equation (6), N represents the number of companies in each event, and t denotes a specific day within the event window ranging from τ_1 to τ_2. We compute CAAR as the cross-sectional average of firms' CAR.

To ensure the robustness of our results, we compute the standardized cross-sectional variance following Boehmer et al. (1991), which is robust to any variance induced by the event (Boehmer et al., 1991; Kolari and Pynnönen, 2010). In Appendix (C) we provide further technical details on the implementation of Boehmer et al. (1991).

IV Sample and data sources

We merge several data sources to analyse how securities react to the impact of extreme weather events. First, we obtain the location of facilities and their link to securities by merging the E-PRTR with Amadeus ownership data from Bureau van Dijk.[9] Second, we match the resulting dataset with daily historical returns and institutional shareholder ownership data over time obtained from Factset. Third, we use facility locations, timing and geographical extension of extreme weather events to identify the time and location of the impact of companies. Additional details on data and matching methodologies are provided in Appendices (E) and (F).

We identified 1,377 impacted facilities from the 4,162 that are linked to public listed companies. Those belong to 353 unique publicly listed companies from a total of 832 companies that were matched and not filtered out. These numbers are consistent with similar studies on physical risks using facility data outside the US (Bressan et al., 2022). The initial sample included around 1000 public listed companies but we implement several measures to enhance the scientific rigor of our analysis. First, when extreme weather events recur multiple times, we only consider those with an

[9] In this version of the paper, we assume that ownership structures within a company do not change for four years. Therefore, we take two snapshots of Amadeus ownership (2018-2022) and extrapolate the ownership backward assuming it remains unchanged until four years prior.

event-free estimation period. This ensures that the initial event is more likely to prompt investors to update their risk preferences. Second, the securities included in the event study have prices above €5 during the estimation period to avoid including penny stocks. Third, the securities excluded are from the financial sector, except for the insurance sector, and have at least 10% free float. These measures account for liquidity and microstructure effects on stocks (Barnett et al., 2021; Barrot and Sauvagnat, 2016).

Most securities included in the event study are mid- to large-cap companies. Figure (3) shows the names of companies impacted by floods and winter windstorms between 2014 and 2022. From the two figures, we see that some major publicly listed US companies are linked through subsidiaries and branches with facilities in Europe.

The sample is materially relevant in terms of economic exposure to physical risk. Companies charachterizing the analysis belong to sectors such as agriculture, manufacturing, utilities, water, and mining. These sectors are highly exposed to weather-related disasters, as shown by Dunz et al. (2021). In the appendix We provide more detailled information on the sample breakdown by industry in the Appendix section (H.a).

(a) WIND (b) FLOOD

Figure 3. Companies impacted by extreme weather events from 2014 to 2021: In Sub-Figure (3a), we show names of all companies impacted by winter windstorms.In Sub-Figure (3b), we show companies impacted by floods in Europe the same timeframe. The size of the font size is linked to the market capitalization of the company.

We identified 353 unique securities impacted by extreme weather events. 139 unique publicly listed companies whose facilities are affected by 16 windstorms. Windstorms are heterogeneously distributed throughout Northern Europe. The average historical maximum 3-second 10m wind gust over time and events is 34 km/h. Where a wind speed of above 30 km/h is considered to be damaging to most European buildings (Prahl et al., 2016) . The event date considered is that of landfall as suggested in (Lanfear et al., 2019). For floods, we find that 319 unique securities are affected by 68 flood events between 2014 and 2021. Most of the events take place in Central and Southern Europe. In the specific 10 in Spain, 8 in Italy, 10 in France, 7 in Greece, and 5 in the United Kingdom, among others.

The number of yearly extreme weather events increased from 2014 to 2022, with floods impacting a larger number of facilities, thus showing a higher EAL.[10] In Table (II) we show the number of facilities impacted by extreme weather events in a breakdown by country, extreme weather event, and EAL as a percentage share of all assets. The first three columns show the facilities impacted by winter storms as an absolute number, as the percent of impacted facilities as a share of the total for that country, and their average EAL over all facilities. The same applies to flood-impacted facilities. Table (II) shows that a greater number of facilities are impacted by floods than by winter storms in Europe. In addition, Great Britain is the country most affected by extreme weather events. On average, the EAL as a percentage share of all assets is considerably larger for floods than for winter storms. Denmark, Germany, and Belgium have an EAL of 0.01, 0.003, and 0.002 percentages, respectively. Thus, showing that the EAL for these events is very low in Europe. However, floods have a higher EAL with Ireland, Austria, and Hungary featuring 14, 12, and 11, respectively. Consequently, for those facilities impacted for which we compute an EAL, floods show a higher EAL than winter storms.

The share of local institutional ownership of the securities characterising the sample largely variates across Europe, but is consistent between the impacted samples and the overall ownership sample. In Figure (4) we see that the share of "Local Ownership" (LO) for securities is heterogeneously distributed throughout the European Union (EU). Some countries have a very high level of LO, and others have a very low one. Two striking examples are Sweden with 90% of LO and Luxembourg with less than 10%.

Although the sample shows heterogeneity in the location of facilities, securities, and securities' owners, we find that many companies linked to European facilities are headquartered in the United States (US). We account for this in our analysis with a robustness check. In the Appendix (F.d) we provide a detailed breakdown of facilities, securities, and IO by country and sample.

[10] Details on the frequency of events are available in Appendix (D).

	WIND			FLOOD			
	Impacted	% Total	EAL_i	Impacted	% Total	EAL_i	Total
AT	-	-	0.00077	30	0.72	12.01	88
BE	21	0.5	0.00243	17	0.41	9.82	187
CH	-	-	0.00111	19	0.46	13.32	55
CY	-	-	0.0017	-	-	-	2
CZ	-	-	0.00134	36	0.86	9.36	104
DE	11	0.26	0.00252	196	4.71	9.98	564
DK	10	0.24	0.01278	3	0.07	8.97	38
EE	-	-	0.00204	-	-	7.51	24
ES	-	-	0.0009	111	2.67	10.1	287
FI	-	-	0.00163	-	-	8.07	121
FR	25	0.6	0.00137	480	11.53	8.3	746
GB	261	6.27	0.00159	580	13.94	8.21	885
GR	-	-	0.00088	1	0.02	8.81	14
HR	-	-	0.00328	2	0.05	9.61	12
HU	-	-	0.00252	-	-	10.62	32
IE	25	0.6	0.00197	23	0.55	13.51	42
IS	-	-	-	-	-	-	3
IT	-	-	0.0005	204.0	4.9	10.46	385
LI	-	-	0.00414	1	0.02	-	1
LT	2	0.05	0.00146	-	-	8.83	6
LU	1	0.02	0.00118	1	0.02	4.2	2
NL	14	0.34	0.00179	34	0.82	9.74	40
PL	-	-	0.00221	21.0	0.5	9.38	312
PT	-	-	0.00117	-	-	8.03	40
RO	-	-	0.0008	15.0	0.36	11.97	45
RS	-	-	0.0006	-	-	9.17	6
SE	3	0.07	0.00214	-	-	10.98	113
SI	-	-	0.00034	-	-	8.81	8
Total/Mean	373	8.96	0.00204	1774	42.62	9.59	4162

Table II. Amount of impacted facilities over total by country: In Table (II), we show the number of impacted facilities by the country location of the facility (Impacted), the country location of the facilities we matched with the matching algorithm (Total) and the percentage of impacted facilities over the country total as %. The reported facilities are only those linked to a public listed company. Additionally, the EAL is the expected annual loss for every facility averaged over the whole country. The row total is presented as the total over the countries presented in the table by weather disaster type. The total is to be interpreted as a mean when below the EAL columns. Impacted and Total are as integers and % Total and EAL are percentages.

V Investors' surprise around extreme weather events

V.a Case studies: Wind storm Ciara and 2021 Summer floods

In the following, we present the results for two case studies to demonstrate the efficiency of the methodology. We selected the case studies following their prominence in the EU in terms of damages. Winter windstorm Ciara in early February 2021 is a case study in an EIOPA report, and summer

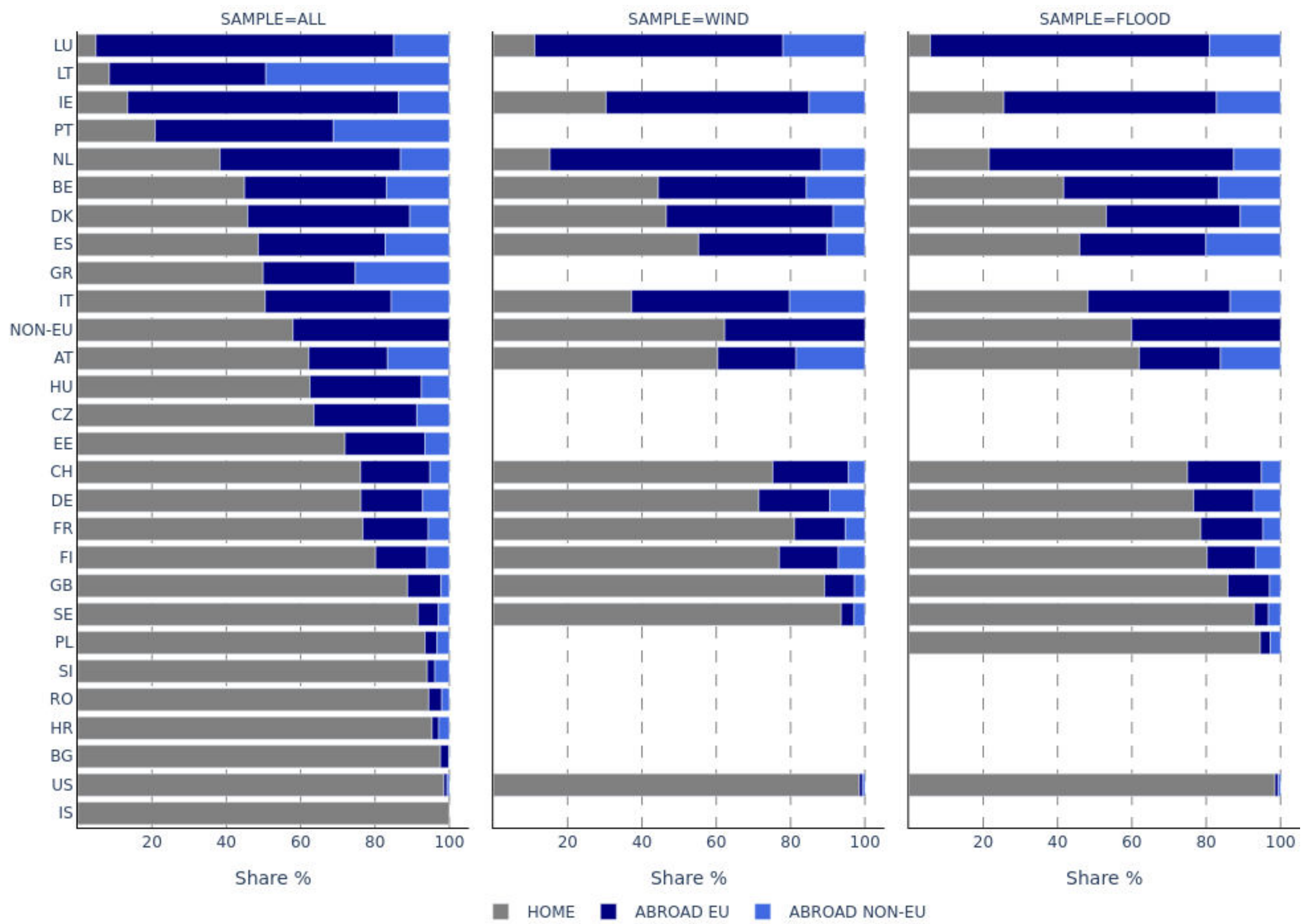


Figure 4. IO ownership of stocks by security Country: In Figure (4), we show the stock ownership by the IO country and extreme weather event. Country ownership is defined in three groups to ease understanding. Ownership of the same country of the security country, or "Home", ownership from another country located within the EU, and ownership of IOs outside the EU. "NON-EU" is a security country category for all securities that have their headquarters outside the EU.

floods in July 2021 are among the most damaging floods in the history of the EU with an estimate of € 10 billion damages (EIOPA, 2022).

Winter storm Ciara and the summer floods in Belgium, Germany, and the Netherlands in July 2021 triggered an average negative investors' surprise on securities prices. In Table (III) we observe CAAR over different expected returns estimation methods for the two case studies. The vertical axis of the table presents the days from the event and is aggregated over three buckets: first from -5 or -2 for winter storms and floods, respectively, to -1 day; second, from the event date to 10 days after the event occurrence; and third from 11 trading days to 22 after the event occurrence. From columns 1 to 4, we present CAAR for every expected return model for winter storm Ciara, and from 5 to 8 the same but for the summer floods in Belgium, Germany, and the Netherlands in 2021. In Table (III) we see that the negative surprise from winter storm Ciara reached -2.72

to -2.91 percentage points (p.p) at and after the event date. The negative surprise also holds for floods; however, it is realised only from 11 to 22 days after the event occurrence, and it reaches the negative CAAR value of -0.6 to -2.16 p.p.

	$CAAR$							
	Windstorm Ciara				Summer floods July 2021			
	Mkt	$3F$	$4F$	$5F$	Mkt	$3F$	$4F$	$5F$
(-5/-2:-1)	-0.81***	-0.85***	-0.83***	-0.78***	0.73***	0.6**	0.45*	0.37
	(0.14)	(0.14)	(0.14)	(0.14)	(0.21)	(0.25)	(0.25)	(0.24)
(0:10)	-2.91***	-2.72***	-2.72***	-2.79***	0.63***	0.29	0.13	-0.16
	(0.27)	(0.29)	(0.29)	(0.32)	(0.24)	(0.27)	(0.29)	(0.29)
(11:22)	-1.38***	-1.71***	-1.37**	-1.66***	-0.61**	-0.74**	-1.54***	-2.16***
	(0.49)	(0.48)	(0.56)	(0.5)	(0.31)	(0.32)	(0.41)	(0.38)
N	39	39	39	39	9	9	9	9

Table III. CAAR for Windstorm Ciara and the Summer floods in July 2021: In Table (III), we show the average $CAAR$ for winter windstorm Ciara and the Summer floods in July 2021 aggregated over the days from the event for all estimation models to estimate expected returns (Mkt, $3F$, $4F$, $5F$). N is the number of observations on which it is computed. The numbers in brackets below the average estimates are standard deviations computed using the test statistics from Boehmer et al. (1991).

We then investigated whether affected companies disclose information on exposure or impact in the annual report following the extreme weather event. In Table (IV) we show excerpts from the 2020 and 2021 annual reports of companies impacted by either winter storm Ciara or the 2021 summer floods. Reading the excerpts, one notices that these companies reported about their exposure to extreme weather events. Thus, we validate our implementation of the methodology of the Statistics Committee of the ESCB (ECB, 2023).

V.b Results: the extreme weather events' sample

Building on the insights obtained from the case studies, we extend our analysis to the entire sample of companies impacted by extreme weather events. The case studies on winter storms and floods showcased the effectiveness of the methodology implemented to detect significant market adjustments in response to these adverse events. Consequently, we do a comprehensive analysis of winter storms and floods testing the hypotheses formulated in Section (II).

By extending the analysis to the whole sample, we find evidence supporting H_1. The first hypothesis stated that *"Securities of Companies impacted by winter wind storms experience more negative cumulative average abnormal returns (CAAR) than those impacted by floods."*. Table (V)

	Source	Annual Report Excerpt
Ciara	OCI (2020)	*"Adverse weather conditions and natural disasters such as hurricanes [...] could result in property damage loss of life, production interruptions and supply chain disruptions"*
	Wienerberger AG (2020)	*"After a weather related weak start to the 2020 business year"*
	Aperam SA (2020)	*"Aperam's manufacturing plant have experienced and may in future experience, plants shutdowns or periods of reduced production as a result of such process failures, or other events such as natural disasters [...] or extreme weather events"*
	SCA (2020)	*"SCA's forest land is spread across large areas of Northern Sweden, which means that forest fires and storms can usually only impact a minor part of the forest portfolio. The forest is therefore not insured."*
Floods 2021	Norsk Hydro ASA (2022)	*"The physical adaptation of assets and supply chain robustness are important mitigating factors against the risk posed by climate change related incidents, such as flooding"*
	Vinci SA (2022)	*"VINCI is highly exposed to the acute physical risks associated with climate change. Extreme weather events can negatively impact the Group's activities in different ways, such as damage to worksites or flooded runways ..."*
	Derichenbourg (2022)	*"A major event in the Recycling Business ([...] prolonged flooding, etc.) could lead to a prolonged breakdown in the logistic chain. Major accident [...] or a natural disaster (earthquake, flood, etc) interrupting operations."*

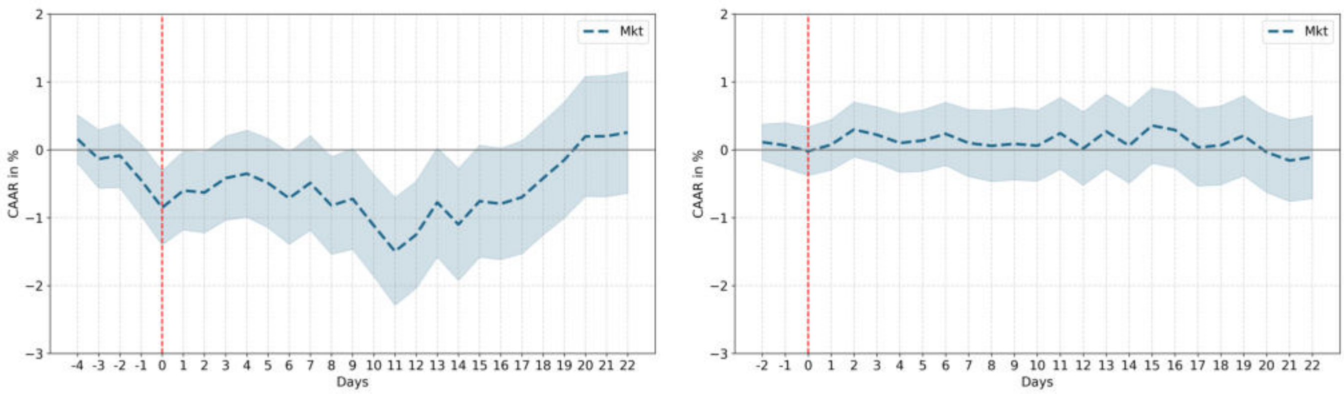
Table IV. Annual reports extracts related to risks from extreme weather events for companies with negative CAAR during windstorm Ciara in 2020 and the summer floods of July 2021: In Table (IV) we show 2021 annual reports' extracts reporting on the risk exposures of the companies impacted by Windstorm Ciara in early February 2020 and from 2021 annual reports reporting on risk exposures of companies impacted by summer floods in July 2021 in Belgium, the Netherlands and Germany.

presents results for the entire sample; however, the interpretation is the same as for Table (III). From Table (V) we see a discrepancy between investors' surprise from floods and windstorms. Investors' surprise from winter storms is consistent over all estimation models. The same is not true for floods, where the negative reaction is limited to the "4F" model by (Carhart, 1997). For windstorms, the CAAR range from -0.94 to -1.22 p.p. at and after the event date. The results from Table (V) support H_1.

	$CAAR$							
	WIND				FLOOD			
	Mkt	$3F$	$4F$	$5F$	Mkt	$3F$	$4F$	$5F$
(-5/-2,-1)	-0.22***	-0.4***	-0.23***	-0.52***	0.08***	0.13***	0.07***	0.11***
	(0.04)	(0.05)	(0.05)	(0.05)	(0.02)	(0.02)	(0.02)	(0.02)
(0,10)	-0.72***	-0.97***	-0.72***	-0.99***	0.06	-0.07	-0.13***	-0.14***
	(0.1)	(0.1)	(0.11)	(0.11)	(0.05)	(0.05)	(0.05)	(0.05)
(11, 22)	-0.61***	-1.21***	-0.67***	-1.08***	0.02	0.29***	-0.11	0.2**
	(0.15)	(0.16)	(0.17)	(0.16)	(0.08)	(0.08)	(0.08)	(0.08)
(-5/-2,22)	-0.59***	-0.97***	-0.61***	-0.94***	0.04	0.12	-0.1	0.04
	(0.15)	(0.16)	(0.17)	(0.16)	(0.08)	(0.08)	(0.08)	(0.08)
N	223	223	223	223	634	634	634	634

Table V. CAAR by hazard day from the event: In Table (V), we show the average $CAAR$ for winter windstorms and floods for the whole spale aggregated over the days from the event for all estimation models to estimate expected returns (Mkt, $3F$,$4F$,$5F$). N is the number of observations on which it is computed. The numbers in brackets below the average estimates standard deviations using the t statistic from (Boehmer et al., 1991).

We provide additional evidence supporting H_1 by plotting $CAAR$ and their confidence interval for the entire event window. In Figure (5) the vertical axes show $CAAR$ in $\%$, while the horizontal axis shows days from the event. The estimates in the graph are only shown for the market model and the confidence interval is obtained using the measure of event-induced variance of Boehmer et al. (1991). The results consistently show that there is a negative cumulative risk adjusted investor reaction to winter windstorms that reaches -1.22 p.p. on the event date and up to -2 p.p. 11 days after the event. For floods, there is no evidence of a significant deviation from zero. Additionally, in the Appendix Section (G.a) we show that the results are persistent over time and are not driven by outliers in specific years such as, for instance, when Covid lockdowns were announced.



(a) WIND (b) FLOOD

Figure 5. CAAR for all weather-related disaster types: In Sub-Figure (5a) we depict CAAR for companies impacted by winter windstorms independent of the location of the facility compared to the headquarters. Finally, in Sub-Figure (5b) we depict CAAR for companies impacted by floods.
The vertical axes show $CAAR$ in $\%$, while the horizontal axis shows days from the event.

V.c The information's advantage

In this section, we analyse whether a higher share of local ownership positively impacts stock prices during extreme weather events. To do so, we test hypotheses two to four presented in Section (II). We start with a baseline model and test whether it holds for different specifications of informational advantage. To test H_2, we analyse the impact of local institutional ownership on CAR in a panel setting. The baseline regression model is based on the impact of $LO_{(i,t-1)}$ on $CAR_{Model,(i,t)}$ and accounts for time fixed effects. We define the baseline model as

$$CAR_{Model,(i,t)} = \beta_0 + \beta_1 LO_{(i,t-1)} + \beta_2 Post + \beta_3 LO_{(i,t-1)} \cdot Post + \Psi_t + \epsilon_{it} \tag{7}$$

Where $CAR_{Model,(i,t)}$ are the CARs for company i on the date of the event t estimated using the models presented in Section (III.d). $LO_{(i,t-1)}$ is the share of local institutitonal security ownership for security i in the quarter prior to the event. $Post$ is a dummy variable if the day of the event is at, or after the event date. Additionally, Ψ_t are time fixed effects that account for heterogeneity due to the event date.

We also test the validity of the information advantage hypothesis over two different channels. First, we expand the baseline model to account for heterogeneity triggered by investors' knowledge of the risk of extreme weather events. We do this by formally testing H_3 and including a triple interaction term between local institutional ownership, exposure, and the days after the event date. In the regression model, we include all necessary double interaction terms that belong to this type of heterogeneity analysis (Olden and Møen, 2022). Consequently, the model to test H_3 is as follows.

$$\begin{aligned} CAR_{Model,(i,t)} = &\beta_0 + \beta_1 LO_{(i,t-1)} + \beta_2 EAL_i + \beta_3 post + \beta_4 LO_{(i,t-1)} \cdot post + \\ &\beta_5 LO_{(i,t-1)} \cdot EAL_i + \beta_6 EAL_i \cdot post + \beta_7 LO_{(i,t-1)} \cdot post \cdot EAL_i + \\ &\Psi_t + \epsilon_{it} \end{aligned} \tag{8}$$

In Equation (8) EAL_i is the company's exposure to the extreme weather event in %.

Second, we test whether distance between the impacted facility and the headquarters reduces the positive effect of local ownership. This model follows the concept elaborated by Pellegrino et al. (2022) where investment barriers increase with distance. We compute the distance between the location of the headquarters and the facility suing latitude and longitude data as in Coval and Moskowitz (2001).

$$\begin{aligned} CAR_{Model,(i,t)} =& \beta_0 + \beta_1 LO_{(i,t-1)} + \beta_2 Dist_i + \beta_3 post + \beta_4 LO_{(i,t-1)} \cdot post + \\ & \beta_5 LO_{(i,t-1)} \cdot Dist_i + \beta_6 Dist_i \cdot post + \beta_7 LO_{(i,t-1)} \cdot post \cdot Dist_i + \\ & \Psi_t + \epsilon_{it} \end{aligned} \tag{9}$$

In Equation (9) we present the model to test H_4 where $Dist_i$ is the distance in kilometres between the impacted facility and the headquarters of the company.

In Table (VI) we provide descriptive statistics of the variables used in the models from Equations (7),(8) and (9) . The $CAR_{it,Model}$ variables and the distance are winsorized. The median value for all $CAR_{it,Model}$ is negative for both windstorms and floods. For floods $CAR_{it,Model}$ has a lower standard deviation than windstorms, while minimal and maximal values are pretty close in both samples. The median $LO_{(i,t-1)}$ for windstorms exceeds the one of floods by ten percentage points, while the volatility is very similar. However, there is a higher $LO_{(i,t-1)}$ density mass closer to the median for floods compared to windstorms. The EAL_i is higher for floods compared to windstorms. Similarly, companies affected by both wind storms and floods have a similar volatility $Distance_i$.

The test on H_2 shows that a higher LO prior to the event's occurrence positively impacts CAR at the event date for those events with greater uncertainty. H_2 is defined as *"The higher the degree of local institutional ownership in a security before an event, the higher CAR at and after the event occurrence."*. We test the hypothesis regressing Equation (7), with time fixed effects and clustering for time as suggested in Petersen (2009), where time is the event date. The results of these regressions are in columns (1) of Table (VII) for winter storms (WIND) and floods (FLOOD) . $LO_{(t-1)}$ is the share of local institutional ownership in the quarter prior to the weather disaster event and has a positive and significant effect on $CAR_{t,Mkt}$ also when interacted with $post$. For WIND we see that a 1 p.p. increase in $LO_{(t-1)}$ leads to a 0.013 p.p. in $CAR_{t,Mkt}$, with this effect increasing after the event, where a 1 p.p. increase in $LO_{(t-1)}$ leads to a 0.023 p.p. increase in $CAR_{t,Mkt}$. Given that $post$ triggers an average decrease in $CAR_{t,Mkt}$ of -2.66 p.p., $LO_{(t-1)}$ mitigates

		$CAR_{it,Mkt}$	$CAR_{it,3F}$	$CAR_{it,4F}$	$CAR_{it,5F}$	$LO_{(i,t-1)}$	EAL_i	$Distance$
WIND	μ	-0.77	-1.12	-0.88	-1.12	42.31	0.00226	2419.24
	σ	5.63	5.59	5.74	5.67	30.77	0.00221	3050.28
	min	-18.68	-18.97	-17.94	-17.83	0.47	0.00000	0.80
	$P_{25\%}$	-3.54	-3.81	-3.75	-3.98	18.43	0.00095	351.54
	$P_{50\%}$	-0.82	-0.91	-0.80	-0.96	33.00	0.00159	785.54
	$P_{75\%}$	1.98	1.62	1.78	1.71	73.42	0.00287	5122.80
	max	13.62	12.55	13.87	12.75	95.96	0.01094	9563.52
	N	5677	5677	5677	5677	5677	5677	5677
FLOOD	μ	-0.15	-0.08	-0.32	-0.15	34.37	9.57	1913.32
	σ	5.01	4.88	5.42	4.93	29.75	3.67	2839.31
	min	-16.95	-15.78	-19.44	-16.06	0.04	3.66	0.50
	$P_{25\%}$	-2.59	-2.57	-2.86	-2.69	12.69	6.89	264.09
	$P_{50\%}$	-0.07	-0.11	-0.21	-0.15	23.53	8.72	513.01
	$P_{75\%}$	2.40	2.37	2.38	2.34	51.06	12.04	1440.87
	max	12.08	12.18	12.92	12.25	97.11	19.49	9474.36
	N	14022	14022	14022	14022	14022	14022	14022

Table VI. Descriptive statistics for the Regression variable: In Table (VI), we show the descriptive statistics for the main variables used in the regressions. N is the number of observations on which the descriptive are based. μ, σ are the mean and the standard deviation of the sample respectively. $P_{25\%}, P_{50\%}, P_{75\%}$ are the relative percentiles of the distribution. The distance is defined in kilometers between the facility and the headquarters, the previous quarter LO, EAL, CAR are all in $\%$. All variables have been winsorized to contain the impact of outliers on the regression outcomes.

this negative effect by approximately 1.3%. This effect is only valid for winter windstorms in all different estimation models (see Tables (XI,XII and XIII) in Appendix (I)). This effect also holds after excluding the year 2020 and the US from the sample.[11]. Consequently, a higher local institutional ownership mitigates the negative impact of uncertainty from extreme weather events.

Testing H_3 three brings mixed evidence supporting it. H_3 stated that *"The positive impact of local security ownership is greater when affected facilities are located in regions with greater exposure to extreme weather events."*. We test hypothesis H_3 regressing Equation (8) and following the same procedure as with the baseline model. The coefficient of interest in this regression is the triple interaction of $LO_{(t-1)} \cdot Post \cdot EAL_i$ which shows that local ownership is less surprised by the event thanks to EAL. The results are presented in columns (2) for winter storms (WIND) and floods (FLOOD) in Table (VII). Column (2) confirms the results of the baseline model for WIND. Additionally, column (2) shows that companies with a higher share of local ownership prior to the event experience a lower negative-risk adjusted returns. The results obtained using the other

[11] The results to the robustness test are in the Appendix section (J), to calc concerns over the impact of Covid and the high US share of ownership in the sample.

models are provided in Appendix (I) in Tables (XI,XII and XIII). Although this effect holds over the different estimation models and after excluding year 2020, the coefficient flips when excluding the US, see the Appendix section (J).

	$CAR_{t,Mkt}$					
	WIND			FLOOD		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
β_0	0.0064	-0.0008	0.1136	0.2610	0.3110	0.1605
	(0.2538)	(0.2565)	(0.2641)	(0.2362)	(0.2250)	(0.2543)
$LO_{(t-1)}$	0.0131***	0.0060	0.0118***	0.0026	0.0014	0.0105***
	(0.0021)	(0.0039)	(0.0043)	(0.0027)	(0.0031)	(0.0035)
$Post$	-2.6585***	-2.0402***	-3.0545***	-0.6898**	-0.7927***	-0.8900***
	(0.3216)	(0.3501)	(0.3317)	(0.2850)	(0.2870)	(0.3046)
$LO_{(t-1)} \cdot Post$	0.0226***	0.0139***	0.0468***	0.0035	0.0062	0.0056
	(0.0030)	(0.0050)	(0.0055)	(0.0038)	(0.0044)	(0.0047)
EAL_i		-52.949**			-0.0220	
		(25.107)			(0.0288)	
$LO_{(t-1)} \cdot EAL_i$		3.1644**			0.0007	
		(1.2943)			(0.0005)	
$Post \cdot EAL_i$		-165.65***			0.0473	
		(35.864)			(0.0341)	
$LO_{(t-1)} \cdot Post \cdot EAL_i$		3.6874**			-0.0018**	
		(1.4834)			(0.0007)	
$Dist$			-9.485e-05**			3.16e-05
			(4.419e-05)			(4.965e-05)
$LO_{(t-1)} \cdot Dist$			9.356e-07			-1.974e-06**
			(9.981e-07)			(8.584e-07)
$Post \cdot Dist$			0.0001			0.0001**
			(6.463e-05)			(6.493e-05)
$LO_{(t-1)} \cdot Post \cdot Dist$			-5.696e-06***			-1.582e-06
			(1.37e-06)			(1.161e-06)
N	5593	5593	5593	14022	14022	14022
R^2	0.0322	0.0514	0.0353	0.0014	0.0020	0.0048
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Table VII. Regression of $CAR_{it,Mkt}$ on $LO_{(i,t-1)}$ and EAL_i, $Dist$: In Table (VII), we show fixed effects regression where $CAR_{it,Mkt}$ is dependent variable. The explanatory variables are: $LO_{(i,t-1)}$ or the quarterly lagged percentage of local IO ownership calculated using the measure by Coeurdacier and Rey (2013) and definitions from Coval and Moskowitz (2001), EAL_i or the expected annual loss. $Post$ which is a dummy equal 1 for the days at or after the event and $Dist$, which is the distance in degrees between the facility and the headquarters as suggested in (Pellegrino et al., 2022). Covariance is clustered by time (Petersen, 2009).

Testing H_4 support the hypothesis. H_4 states that *"The positive impact of local security ownership will weaken with increasing distance between a facility and the headquarters of the company*. We test hypothesis four regressing Equation (9) under the same conditions as for the other models. In this specification, we are particularly interested in the triple interaction $LO_{(t-1)} \cdot Post \cdot Dist$ as this shows that the positive impact of the information advantage decreases with the distance from the headquarters, which are by definition closer to the local institutional owners. The results of this specification are presented in columns (3) for winter storms (WIND) and floods (FLOOD) in Table (VII). Column (3) confirms the results of the baseline model for WIND. Additionally, column (3) shows that the interaction term is negative and decreases the information precision with increasing distance. For example, for a distance of 1000 km, then CAR will be more negative by 0.05 p.p. for every increase in p.p. in $LO_{(t-1)}$. Thus supporting H_4. The results obtained using the other models are provided in Appendix (I) in Tables (XI,XII and XIII). These results also hold after accounting for both robustness tests.

VI Conclusion

Our analysis explores how extreme weather events impact securities prices and whether the surprise is influenced by informational advantages. We compare winter storms and floods since early warning systems show that they have different types of impact and uncertainty about location. Our empirical methodology provides a robust framework for understanding these dynamics. Thanks to the empirical setting, we investigate how information on risk exposure and distance influence the informational advantage of local owners.

For storms, we find a negative cumulative average risk-adjusted abnormal daily return of 99 basis points on the event date. Local institutional ownership (IO) reduces this negative surprise by 1.3% for every additional percentage point of local ownership. Drawing from the findings summarised above, our research substantiates the theories posited in the literature (Kruttli et al., 2023; Van Nieuwerburgh and Veldkamp, 2009; Coval and Moskowitz, 2001). This empirical validation echoes previous studies and contributes to our understanding of the relationship between extreme weather events and the prices of securities (Kruttli et al., 2023; Huynh and Xia, 2021; Alok et al., 2020). These results are in line with the literature (Kruttli et al., 2023; Blanco et al., 2024; Pellegrino et al., 2022).

The reason why local investors are less surprised by closer extreme weather events is of multiple nature and we add to a lively debate. For example, better stock performance is explained by the ability of investors to acquire information on signals, since local asset managers are better at picking the right companies (Coval and Moskowitz, 2001). However, this knowledge becomes counterproductive if it is surprisingly negative for investors (Alok et al., 2020). Another explanation is that investors follow local analysts whose performance in predicting companies' resilience to extreme weather events improved over time. For example, Pankratz et al. (2023) show that investors often followed analysts' advice also when they did not account for the negative impacts of extreme temperatures. Kruttli et al. (2023) show that analysts actually ask about damages after events occur, while Faralli (2024) shows that analysts improve over time.

Our work has several limitations, as we miss analyst data to precisely assess to which extent facilities are impacted, and we do not have specific information on the importance of facilities for the company owners. The issues with the data sources used in our analysis are that although the extreme weather event data are very precise and we can correctly assess the potential expected damage, we do not have information about the relevance of facilities for the companies' production process. However, in Kruttli et al. (2023) this approach does not lead to different results and the facilities reported in the E-PRTR are usually relevant facilities for the reporting companies.

We contribute to two streams of literature. First, we analyse the role of local institutional ownership on securities performance under exogenous shocks. Our analysis is performed under market segmentation and event-driven uncertainty. The second is one that analyses the impact of extreme weather events on asset prices using granular facility data. Here we contribute using innovative data and open source data for financial analysis.

The implications of our findings are also significant for policy makers and finance practitioners alike. For policy makers, our research underscores the value of publicly available sources, such as E-PRTR and Copernicus, in facilitating climate finance analysis. However, our study highlights the need to harmonise data between countries to enhance the accuracy and comprehensiveness of such sources. For finance professionals, the presence of informational barriers and local equity preference in driving market adjustments after extreme weather events underscores the need for portfolio holders to consider these limitations when formulating their investment strategies.

In conclusion, our study lays the foundations for future research efforts in climate finance. We encourage researchers to extend this type of analysis to other countries that possess PRTR locational data, allowing a broader assessment of the impacts of extreme weather events on financial markets. In particular, it is interesting to investigate the impact of disclosure on insurance policies on market agents. The presence of state insurance policies, such as in France, also affects market dynamics, especially in flood-prone regions. Lastly, we advocate for an interdisciplinary approach that combines insights from finance, climatology, and economics to unravel the intricate interplay of extreme weather events, investor behaviour, and financial markets.

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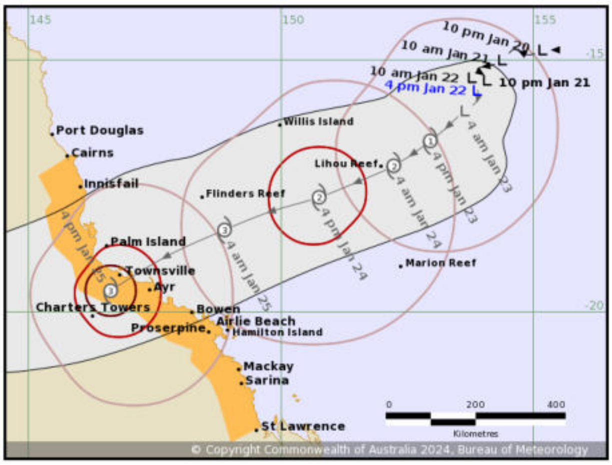
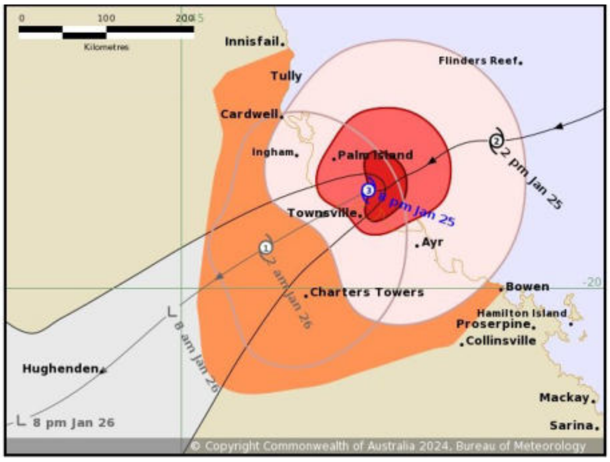
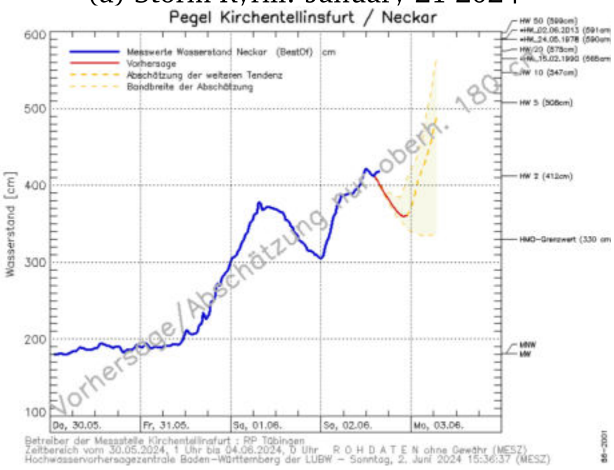
A Early warning signals floods and storms



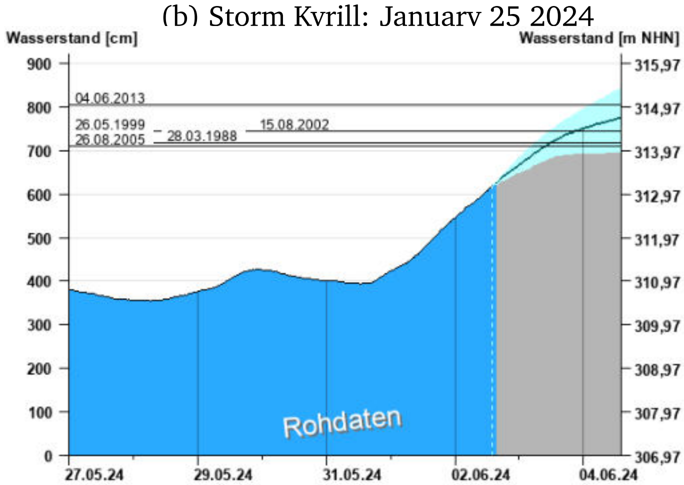
(a) Storm Kyrill: January 21 2024



(b) Storm Kyrill: January 25 2024



(c) Flood Neckar: June 2 2024



(d) Flood Donau: June 2 2024

Figure 6. An example of early warning systems with storms and floods: In Sub-Figure (6a) and (6b) we see one of the first and last forecasts of tropical storm Kyrill in Queensland Australia in late January 2024. The preicted area of impact narrows down over time and the timeframe of prediction is of around 5/7 days. In Sub-Figure (6c) and (6d) we see the timeframe of water level prediction as well as the water level compared with major historical floods for rivers in the regions of Baden-Wuerttenberg and Bavaria in Southern Germany in June 2024. The timeframe of prediction is very short, 2 days max and the uncertainty about the expected water level very limited. Sources: Australian Government, Federal states of Bavaria and Baden-Wuerttenberg.

B Assessing the quality of the matching algorithm

The Gradient boost shows a ratio of 87% true positives with a relatively low standard deviation. When looking at the *F1* ratio, the gradient boost method remain the second best measure. The gradient boost method shows the best efficiency for the area under the curve (AUC) across all models. We compare all classification algorithms with the receiver operating characteristic (ROC) curve and the AUC as shown in Figure (7). The classification method is better the steeper the curve is on the left part of the plot, or closer to the point (0,1). Additionally, a better performing model features a larger area under the curve (AUC), as is 0.5 for a random model and 1.0 for a model that is perfectly classifying observations. In Figure (7) the Adaboost, the gradient boost and the random forest classifiers have the largest AUC. Nevertheless, the Gradientboost has the lowest standard deviation across the cross validation samples.

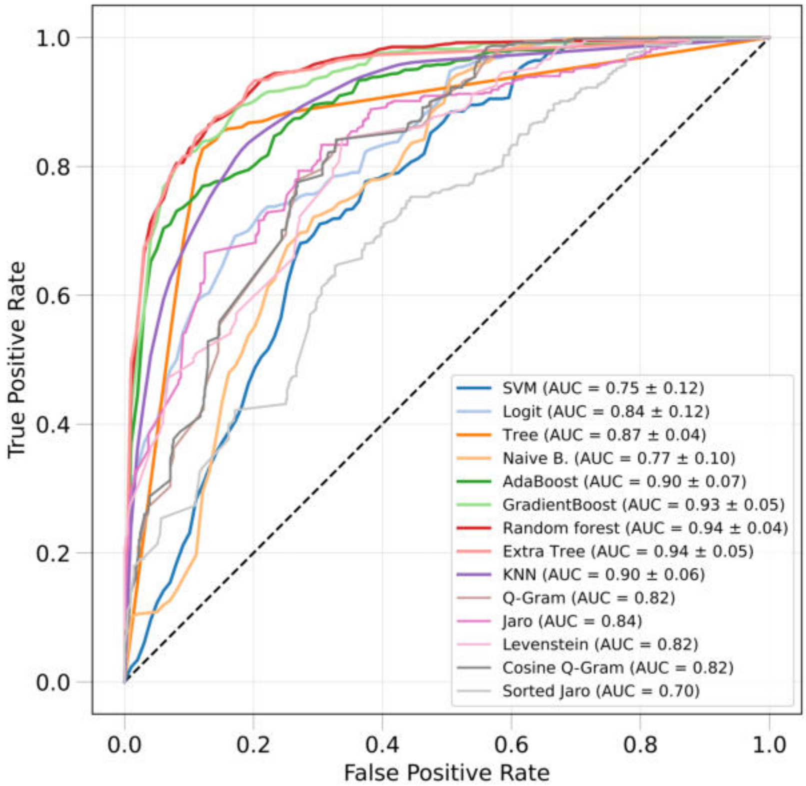


Figure 7. ROC curve of several ML models: Figure (7) shows the AUC for all classification models tested to assess a merge between two company names. The methods presented are the linear support vector machine (SVM), the logit classification, the random tree model (Tree), the Naive Bayes classification model, the Ada boost, the gradient Boost, the random forest and the extra tree classification model together with the k-nearest neighbour model. Additionally we also measure the AUC for the measures underlying the machine learning classification models such as the Q-Gram, the Jaro winkler method and the Levenstein measure.

C Boehmer, Musumeci, and Poulsen test statistic

We compute a parametric test resilient to event-induced variance following (Boehmer et al., 1991) for abnormal returns on the cross sectional dimension of the data where we test whether H_0 : $E(AAR) = 0$ by computing the following test statistic.

$$t_B = \frac{1}{N}\sum_{i=1}^{N} SR_{i,E_t} \Bigg/ \sqrt{\frac{1}{N(N-1)}\sum_{i=1}^{N}\left(SR_{i,E_t} - \sum_{i=1}^{N} SR_{i,E_t}\right)^2} \tag{10}$$

where:

- i=Company
- E_t=Event day t in the event window
- N is the number of companies
- R_{m,E_t} market return at event at event day t
- $\bar{R}_m$ average market return during the estimation period
- $R_{m,t}$ market return on day t
- $\hat{s}_i$ security's i estimated standard deviation of AR_t during the estimation period
- SR_{i,E_t} is the security i's standardized residual on the event day

$$SR_{i,E_t} = AR_{i,E_t} \Bigg/ \hat{s}_i \sqrt{1 + \frac{1}{T_i} + \frac{\left(R_{m,E_t} - \bar{R_m}\right)^2}{\sum_{t=1}^{T_i}\left(R_{m,t} - \bar{R_m}\right)^2}} \tag{11}$$

One can expand this test statistic to the factor models following (Kolari and Pynnönen, 2010).

D The frequency of extreme weather events over time

In our analysis we focus on the hazards that are mostly relevant for Europe in terms of damages: floods and winter storms. These hazards have caused significant damage to European economies in the last decades (EIOPA, 2022). There is also an increasing Trend in terms of damages as highlighted by the 8th EAP report from the European Environmental Agency. In Figure (8) we show that also in the timeframe analysed there seems to be an upward trend in the frequency of extreme weather events.

The sample of extreme weather events we analyse from 2014 to 2022 shows an increase over time. In Figure (8), we plot the frequency of extreme weather events on the vertical axis and the year of occurrence on the horizontal one. The regression line indicates the trend of the occurrences over time by weather-related event type. Comparison of the time trend for floods and windstorms shows that the increase in event occurrence is more pronounced for floods (FLOOD) than for windstorms (WIND).

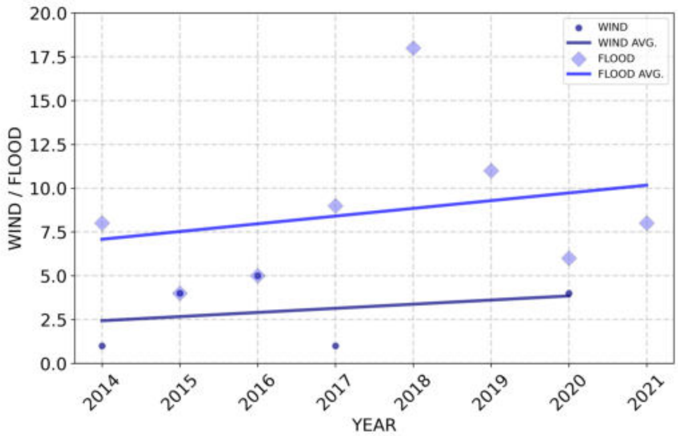


Figure 8. Hazards frequency by year and type: In Figure (8), we show the frequency of extreme weather events in Europe by year. On the y-axis the frequency is an absolute number.

E An example: overlaying floods and facilities' to identify impacted companies

To identify which companies own facilities in an area that has been potentially flooded we combine several databases. For instance, in the E-PRTR we find the location of production facilities, in Amadeus we track the ownership structure, in Factset the prices' time series and from the Archive of the Dartmouth Flood Observatory Brakenridge (2021) we know about the extension and severity of the floods. An overview showing the strengths and weaknesses together with the information about how sources are merged together is provided in Figure (9).

From the E-PRTR, we have yearly information about the facilities' ownership. The E-PRTR database provides information about the company name of the direct facility owner, geographical location and whether this facility is still active from 2008 to 2022. From Amadeus (Bureau van Dijk) we derive whether a company is directly listed in the stock exchange or indirectly, thus being a subsidiary of a directly listed company or the immediate shareholder (ISH), Domestic Ultimate

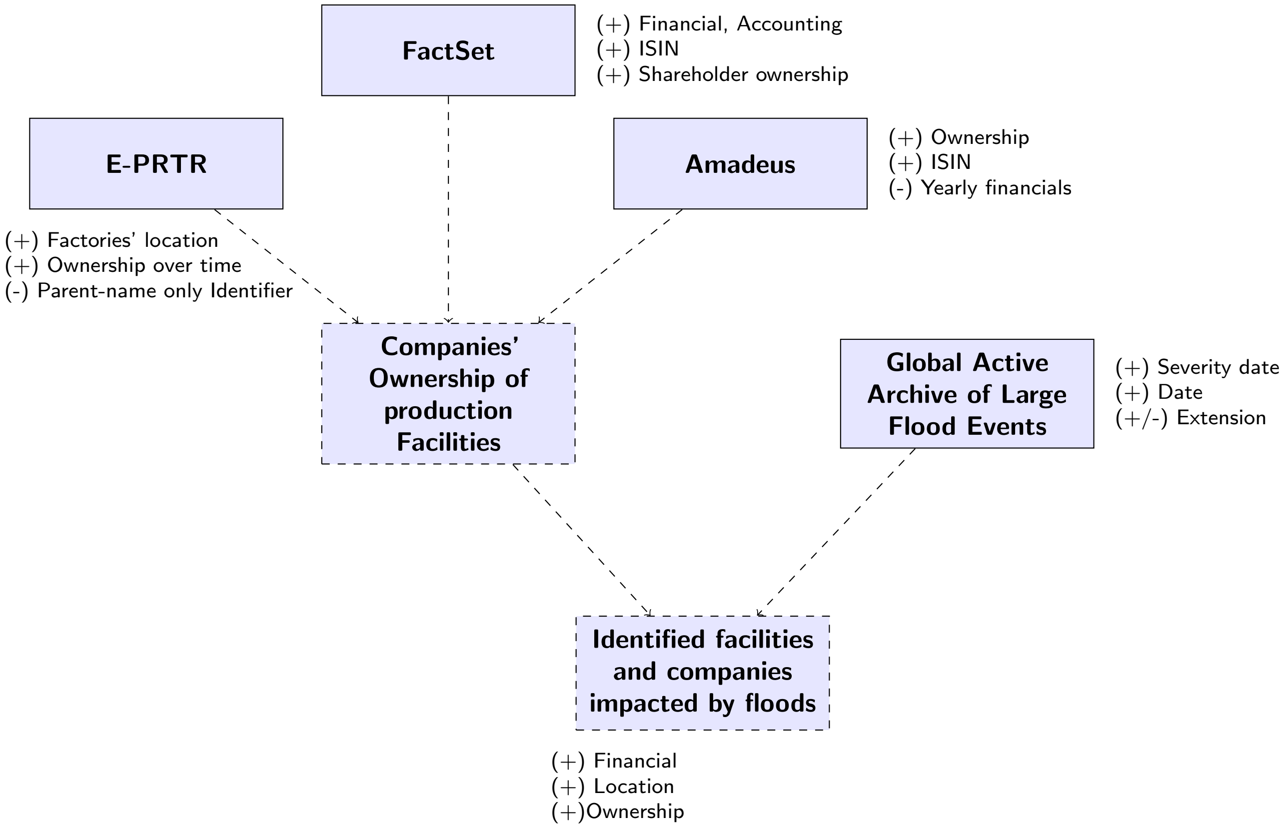


Figure 9. Diverse data sources contribute to the identification strategy: the map shows different sources that charachterize the dataset underlying the analysis: Floods from (Brakenridge, 2021), the (E-PRTR) for the facilities and Amadeus and Factset for the Financials. Dotted lines indicate a merging process. Dotted box borders indicate the resulting dataset of a merging process.

Owner (DUO) or Global Ultimate Owner (GUO). Amadeus applies the 50% ownership rule to decide which company is the Global- or Domestic Ultimate Owner (GUO/DUO) of a company. Moreover, Factset provides among others information about the different components of a company's balance sheet, the stock prices developments as well as its market capitalization. Finally, from Brakenridge (2021) we know the size, severity, duration, extension and exact geographical location of severe flood events. Where the severity is divided in three classes going from the least severe, or SEV CLASS 1, to the most severe, or SEV CLASS 2. The concepts of severity is also related to the damages it caused in terms of physical and human capital as well as the recurrence of this type of event. Usually, a severity class of one means that the last time a similar event occurred less than two decades ago while a severity of two indicates that a similar event happened more than a century ago.

To identify companies impacted by floods we first merge companies' information together (E-PRTR, FactSet, Amadeus) and then geographically join them with the extent of geographic regions affected by flooding. At first we merge the names of the facilities' owners from the E-PRTR every year with the names of all companies included in Amadeus. We then merge the resulting database using the ISIN variable included in Amadeus with all other financial information provided by Factset. The resulting database which has the Latitude and Longitude of every single facility is then overlayed with the extent of geographic regions affected by flooding, thus giving us the relevant information about which facility in a given year was impacted by a flood. In addition, we geocode the location of the headquarters to compute the distance between the facilities and the headquarters.

F Sample: the sources in detail

Our sample is characterised by publicly listed European companies that at the time of a flood had facilities in a region affected by flooding. Understanding which facilities have been affected by an extreme weather event is crucial to understanding how investors react to this type of event. We cover all countries in the European Union (27) and Great Britain.

F.a Financial measures

We obtain data on stock prices and market capitalisation, together with institutional stock ownership holdings from *FactSet financial data and analysis*. The final sample of unique publicly listed companies whose facilities are impacted by extreme weather events is extrapolated from a sample of 3653 daily returns for each firm. The sample is cleaned from financial companies and companies that have less than 10 % free float.

F.b Facilities

The EPRTR is defined in Article 1 of the European Pollutant Release and Transfer Register (E-PRTR) as "an integrated pollutant release and transfer register at Community level [...] in the form of a publicly accessible electronic database and lays down rules for its functioning, in order to implement the UNECE Protocol on Pollutant Release and Transfer Registers [...] and facilitate public participation in environmental decision making, as well as contributing to the prevention and reduction of pollution of the environment". According to Article 5 of the E-PRTR Regulation all operators of facilities that undertake one or more of the activities set out in Annex I to the E-PRTR Regulation are obliged to report specific information if they exceed specific capacity thresholds contained in the register. This means that many companies are obliged to report their locations. In addition, the activities cover, for instance, the energy sector, the production and processing of metals, the mineral industry, the chemical industry, waste and wastewater management, paper and wood production and processing, intensive livestock production and aquaculture, animal and vegetable products from the food and beverage sector, and other activities.

We derive information on the location of facilities from the E-PRTR. The E-PRTR is a public inventory of data submitted by facilities on the amount of toxic chemicals they release on site to air, water, and land; recycled; burnt for energy recovery; and transferred off-site for recycling, energy recovery, treatment, or disposal. One of the most important applications of PRTRs is their use to inform decisions, gain insight, identify opportunities, and evaluate progress related to sustainability of facilities owned by different companies. We are interested in the data set because, to our knowledge, it is one of the few sources available providing information about the same facility over time. Since 2007 the register has expanded and improved and currently contains around 94,000 facilities of European pollutants. Additionally, not every country is covered every year, and not all countries report the same type of information. Consequently, not all variables are consistently populated over time, but for the location, the ownership of the facilities together with the amount of waste produced. With our preliminary merge procedure, we achieved to merge around 21,000 unique facility owners and 34,126 unique facilities. However, many facility owners are not publicly listed.

The E-PRTR covers several industrial sectors but not all facilities for every company in the respective sector. In the E-PRTR we find facilities from the energy sector, the production and processing of metals, the mineral industry, the chemical industry, the waste and wastewater management, the paper and wood production and processing,the intensive livestock production and aquaculture, animal and vegetable products from the food and beverage sector and other activities. Facility operators are required to report the amount of waste produced by their facilities if the production quantity of the facility goes above a predefined capacity threshold. For example, if a company owns a facility in ferrous metal foundries, it should report the amount of waste that you produced if production capacity exceeds 20 tons per day. However, for some industries in the

E-PRTR, there is no capacity threshold requirement[12]

F.c The Ownership Structure of Companies

Information on the ownership structure of companies and shareholder holdings is obtained over time from *Amadeus* from Bureau van Dijk. We track ownership links between subsidiaries and owners. Amadeus provides information on the ultimate ownership of companies and active links. To reconstruct ownership over time, we use a method suggested by (Kalemli-Ozcan et al., 2019), hence to use several vintages (point in time observations) provided by Amadeus. In Amadeus we collect across 2 Vintages (2018 and 2022) around 35 Millions active ownership links. These two point in time snapshots are assumed to hold for the 4 year leading to the snapshot. As such years from 2014 to 2018 feature the ownership structure from 2018 and similar holds for the 2022 vintage.

To analyse how investors react to extreme weather events we find ownership's links between the E-PRTR facility owner and the closest public listed company in terms of ownership structure. We take the first publicly listed stock in the ownership chain of a facility and then compare whether it is located in the same country as the facility or not. The ownership chain that we choose in Amadeus is the 50% of ownership to declare a company to be the ultimate owner of another one.

F.d Facilities, securities and Institutional owners (IO)

Table (VIII) shows the percentage of ownership with a breakdown by ownership category with respect to the location of the facility, security, and security owner. This breakdown is provided for three samples, the one of the E-PRTR facilities that we succesfully linked to securities ("SAMPLE = ALL"), the one of the facilities impacted by wind storms ("SAMPLE = WIND") and the one of the facilities impacted by floods ("SAMPLE = FLOOD"). Home is the country of the company issuing the security. Depending on the location of the facility or of the institutional security owner (IO), these can be in different regions of abroad or share the same location of the security. For example, if the IO, the security and the affected facility are located in the same country, then the column in the table will be characterised by the title *"H"*. If the IO and the security are home and the affected facility is abroad then the column will be *" A(F)"*. If the impacted facility and the security owner are

[12] More information on general applications for PRTRs and on the requirements for companies to be included in the register are available in (Environment Directorate, 2017; European Commission, 2006)

located in two different countries abroad then this column will be *"A (I<>F)"*. Table (VIII) shows that there is enough geographical ownership variation in the sample. For 50% of the facilities in the sample The owner and the traded security linked to them are located in the US. Comparing the three samples presented in (VIII) we do not find major differences between samples.

	ALL					WIND					FLOOD				
Home Country	H	A(I<>F)	A (I=F)	A (I)	A (F)	H	A_(I<>F)	A (I=F)	A (I)	A (F)	H	A_(I<>F)	A (I=F)	A (I)	A (F)
GB	6.77	0.3	0.27	0.23	9.76	8.93	0.25	0.25	0.89	8.93	3.11	0.58	0.8	0.51	4.73
FR	1.72	0.11	0.25	0.12	1.66	4.41	0.38	1.73	0.21	4.75	8.44	0.31	0.93	0.77	2.15
DE	1.27	-	0.21	0.1	1.12	0.24	0.29	1.32	-	1.95	2.58	0.35	1.04	0.4	2.22
SE	0.93	-	-	-	1.11	2.01	-	-	-	2.11	-	-	-	-	0.91
CH	0.62	0.12	0.43	-	1.52	-	0.33	0.49	-	2.28	1.19	0.59	0.59	0.13	4.5
RoW	0.31	0.4	0.25	0.16	0.68	0.06	0.42	0.4	0.23	0.34	0.01	0.54	0.41	0.11	0.26
FI	0.25	-	-	-	0.18	-	-	0.23	-	0.67	-	-	-	-	0.26
PL	0.24	-	-	-	-	-	-	-	-	-	0.78	-	-	-	-
IT	0.11	-	-	-	-	-	-	-	-	-	0.14	-	0.36	0.12	0.16
AU	-	-	-	-	0.17	-	-	-	-	0.32	-	-	-	-	0.13
CA	-	-	-	-	1.08	-	-	-	-	1.17	-	-	-	-	0.81
ES	-	-	0.12	-	-	-	-	-	-	-	0.35	-	0.14	0.14	-
IE	-	-	0.13	-	-	-	-	0.29	-	-	-	-	0.34	-	0.11
IN	-	-	-	-	0.18	-	-	-	-	-	-	-	0.14	-	0.28
JP	-	-	0.13	-	3.1	-	0.1	0.19	-	1.23	-	0.26	0.41	-	2.93
MY	-	-	-	-	0.23	-	-	-	-	-	-	-	-	-	-
NL	-	-	0.21	-	0.11	-	-	0.22	-	-	-	0.18	0.49	-	0.13
NO	-	-	-	-	0.14	-	-	-	-	0.89	-	-	-	-	0.25
US	-	0.22	0.59	-	62.23	-	0.7	2.44	-	47.57	-	0.69	2.07	-	49.6
ZA	-	-	-	-	0.13	-	-	-	-	-	-	-	-	-	0.35
BE	-	-	-	-	-	0.21	-	0.26	-	0.12	0.11	-	-	-	-
DK	-	-	-	-	-	0.18	-	-	-	-	-	-	-	-	-
LU	-	-	-	-	-	-	-	-	-	-	-	-	0.13	-	-

Table VIII. Ownership of Stocks with a break down by location of the facility, IO and security by security country: In Table (VIII), we show the stock ownership with a breakdown by the weather disaster type IO-, facility- and security-country. The ownership of the country is defined into six groups to ease visualisation. When the affected facility, security and IO share the same country, then they belong to "H". When impacted facility and security but IO share the same country they belong to "A (I)". When security and IO but the affected facility share the same country they belong to "A (F)". When security is home, but the IO and affected facility are in the same country they belong to " A (I=F)". Finally, When security is home but IO and impacted facility are two different countries they belong to "A (I<>F)". For every type of weather-related disaster, there are two plots, one with and one without the US because the US is an outlier in terms of ownership stake.The home country category "RoW" stands for all other countries whose ownership with respect to securities and facilities is distributed in the "Rest of the World"

F.e Winter Windstorms

We compute the exposure of companies to winter windstorms in Europe using the windstorms' footprints from the Climate Data Store provided by the Copernicus Programme.[13] The dataset provides climatological indicators on European winter windstorms and their economic impact derived from ERA5 reanalysis. We focus on winter windstorm footprints as they are defined as the maximum 3-second 10-m wind gust speed (in m s-1) over a 72-hour period at each model grid point for a significant winter storm. As such, a storm footprint shows the spatial distribution of maximum wind gust speed for a storm crossing the area of interest.

The C3S storm footprint dataset consists of footprints from all identified winter storms, by the Storm Tracking module, over the period 1979-2021 (van den Brink, 2020). Some years are excluded from the dataset as they did not exceeded the selection criteria threshold of 25m/s 10m winds over land using a 3-degree sampling region. For this reason our sample misses year 2018 and 2019. Due to the timeframe considered in our analysis we only include those storm footprints from 2014 to 2021. Figure (10) shows all areas and an relative windstorm speed of all windstorms that impacted Europe from 2014 to 2021. In Sub-Figure (10b) we show the footprint of Storm Ciara that impacted Europe from February 7 to February 11 2020 and had particular damaging effects on the impacted areas.

(a) Windstorms (2014-2021)

(b) Storm Ciara (7-11 Feb 2020)

Figure 10. Winter windstorms in Europe from 2014 to 2021: In Sub-Figure (10), we show the areas and intensity of winter windstorms that impacted Europe from 2014 to 2021. In Sub-Figure (10b) we show the area that was impacted by the winter windstorm Ciara from February 7 to 11 2020. The different colors show different levels of 10 Minutes Wind Speed in the different areas. The darker the surface the stronger the wind speed.

[13] You can find more information under Copernicus Programme

Our sample consists of 16 windstorms, which are heterogeneously distributed throughout Northern Europe as shown in Figure (10). The average historical the maximum 3-second 10m wind gust over time and events is 34 km/H. A windspeed of above 30 mk/h is considered to be damaging for most European buildings (Prahl et al., 2016) . The event date is considered the one of landfall as suggested in (Lanfear et al., 2019).

F.f Floods

To compute the exposure of companies to floods we use information provided in form of polygons by Brakenridge (2021). The database provides global coverage of the strongest flood events happened in history and an estimate of the land surface coverage. The floods are listed by the severity of the event and the Severity Class assessment is on a 1 to 2 scale. The floods are divided into three severity classes. Class 1 events are large flood events that caused significant damage to structures or agriculture, fatalities and/or featured a 1 to 2 decades long reported interval since the last similar event. Class 1.5 events are very large events with a greater than 2 decades but less than 100 year estimated recurrence interval, a local recurrence interval of 1 to 2 decades and that are affecting a large geographic region (e.g. > 5000 sq. km). Class 2 events are extreme events with an estimated recurrence interval greater than 100 years.

We restrict our sample geographically and over time. The flood data-set has a global coverage and starts in 1985. Nevertheless, our geographical coverage extends to to the floods that might impact the facilities recorded in the E-PRTR database. Additionally, as far as our time-frame is concerned we are constrained by our interest of investors' reactions after the Paris agreement.

Our flood sample consists of 68 flood events, which are heterogeneously distributed. 35 events have a severity class of 1.5, 27 events of 1.0 and 6 events with a severity class of 2.0.The geographic distribution of events is very heterogeneous. From Figure (11) we can see that most of the events take place in central and southern Europe. In the specific 10 have Spain as the main country, 8 Italy, 10 France, 7 in Greece and 5 in the United Kingdom among others. In Sub-Figure (11b) we also include a picture for the case study on the summer floods in the Belgium, germany and the Netherlands in July 2021, which impacted several regions. The event is classified as event of severity class 2.

(a) Floods (2014-2021)

(b) Floods (13 - 15 Jul 2021)

Figure 11. Floods in Europe from 2014 to 2021: In Sub-Figure (11), we show the areas and severity of floods that impacted Europe from 2014 to 2021. In Sub-Figure (11b) we show the area that was impacted by the summer floods in the Belgium, Germany and the Netherlands in Jul 2021. The different colors show different levels of severity by polygon. The darker the lower the recurrence of such a flood event in the area.

G Additional Results

G.a CAAR over years and event types

Our results are also persistent over time and not driven by a specific outlier year as the one where Covid lockdowns have been announced. In Table (IX) the horizontal axis shows CAAR averaged over the course of a year while the vertical one shows the results for different event window buckets with a breakdown by weather related event type. In Table (IX) we showed that after the event, CAAR are negative and significantly different from zero for each year. The only exception to this result are 2016 for winter windstorms and 2014,2015,2018 for floods. Additionally, we find that results are consistently larger for winter wind storms.

		$CAAR$							
	Days	2014	2015	2016	2017	2018	2019	2020	2021
WIND	(-5:-1)	-0.18**	-0.52***	0.28***	-0.16	-	-	-0.73***	-
		(0.07)	(0.08)	(0.1)	(0.12)	(-)	(-)	(0.13)	(-)
	(0:10)	-1.6***	-0.72***	2.98***	-1.2***	-	-	-2.67***	-
		(0.14)	(0.2)	(0.23)	(0.25)	(-)	(-)	(0.26)	(-)
	(11:22)	-1.65***	-1.39***	2.59***	-2.1***	-	-	-1.0**	-
		(0.26)	(0.23)	(0.33)	(0.6)	(-)	(-)	(0.46)	(-)
	N	85	27	40	20	-	-	43	-
FLOOD	(-2:-1)	-0.08	2.94***	0.22***	-0.36***	0.3***	-0.08**	0.03	-0.19
		(0.05)	(0.08)	(0.03)	(0.04)	(0.07)	(0.04)	(0.09)	(0.07)
	(0:10)	0.28**	4.03***	-0.25**	0.27***	0.14	-0.64***	-1.22***	-0.49
		(0.12)	(0.13)	(0.1)	(0.08)	(0.17)	(0.11)	(0.28)	(0.14)
	(11:22)	0.92***	5.13***	0.05	-0.29**	0.6**	-1.79***	-0.67	-1.01
		(0.24)	(0.21)	(0.15)	(0.13)	(0.24)	(0.16)	(0.45)	(0.24)
	N	61	28	126	181	103	40	23	63

Table IX. CAAR by hazard, year and day from the event: In Table (IX), we show the average $CAAR$ for winter windstorms and floods aggregated over the days from the event by year of event occurrence and the Mkt estimation models to estimate expected returns. N is the number of observations on which it is computed. The numbers in brackets below the average estimates are p-values computed using the Wilcoxon signed rank test if the number of unique companies is below 30 in the sample.

H Industry analysis

H.a Extreme weather events: industries

Here we show the number of facilities by NACE sectors. MSCI in a recent publication showed that sectors as Manufacturing, Utility, Water, and Mining are sectors that are highly exposed to climate hazards of different types. These sectors are highly represented in the sample we matched with the E-PRTR. The Manufacturing sectors are around 20% of all facilities that are owned by public entities and are affected by extreme weather events. The other sectors also characterised the majority of the facilities impacted. In Table (X) we provide an overview of the facilities impacted by extreme weather events as a percentage of the whole sample.

	All companies			Listed companies		
	Impacted	Total	% Total	Impacted	Total	% Total
ADMINISTRATIVE	570.0	1163.0	1.78	52.0	90.0	1.29
AGRICULTURE	282.0	904.0	0.88	10.0	31.0	0.25
COMMUNICATION	99.0	233.0	0.31	18.0	44.0	0.45
CONSTRUCTION	356.0	762.0	1.11	18.0	46.0	0.45
EDUCATION	11.0	16.0	0.03	NaN	NaN	NaN
ENTERTAINMENT	27.0	69.0	0.08	1.0	1.0	0.02
FINANCIAL	446.0	798.0	1.39	34.0	82.0	0.85
HEALTH	537.0	1291.0	1.68	NaN	NaN	NaN
MANUFACTURING	7412.0	15488.0	23.14	766.0	1972.0	19.05
MINING	172.0	501.0	0.54	92.0	287.0	2.29
OTHER	116.0	207.0	0.36	42.0	52.0	1.04
PUBLIC	141.0	242.0	0.44	8.0	8.0	0.20
REAL ESTATE	322.0	634.0	1.01	3.0	6.0	0.07
SALES	1002.0	2221.0	3.13	67.0	170.0	1.67
SERVICE	76.0	159.0	0.24	1.0	1.0	0.02
TECHNICAL	530.0	1122.0	1.65	46.0	110.0	1.14
TRANSPORTATION	216.0	515.0	0.67	33.0	67.0	0.82
UTILITIES	575.0	1427.0	1.80	179.0	455.0	4.45
WATER	1965.0	4274.0	6.14	337.0	599.0	8.38
Total	14855.0	32026.0	46.38	1707.0	4020.0	42.46

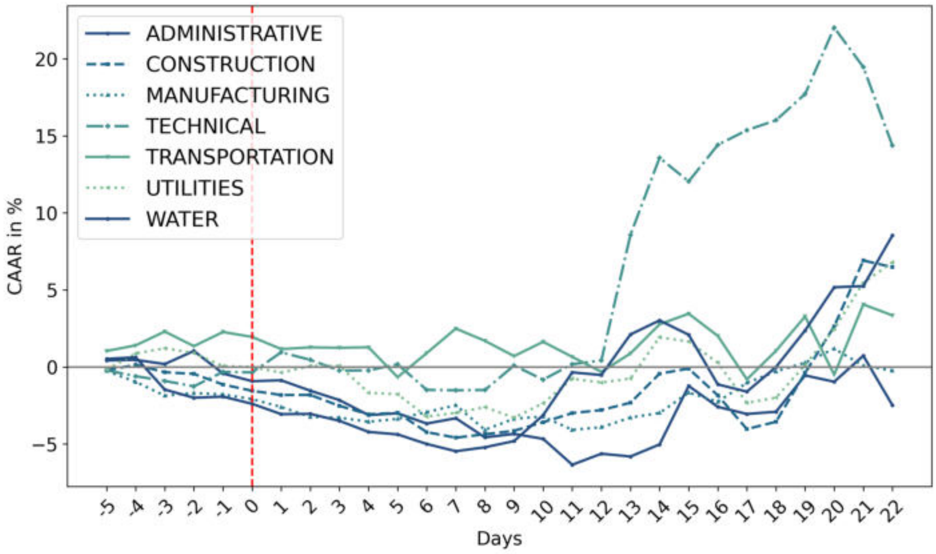
Table X. Impacted facilities by NACE category from 2014-2021 for all hazards: In this table, we show the number of unique facilities for which we could follow the ownership structure by NACE category. In the first 3 columns we show the impacted facilities, the total number of facilities we match and the percentage of facilities impacted over the total of 32,026.In the last 3 columns we show the same numbers but only for those facilities that have a public listed company in the ownership structure.

H.a.1 The Case studies

In Figure 12 we report the CAAR for windstorm Ciara and we see that CAAR are mostly negative and persistent over a longer period for three main NACE categories: Construction, Manufacturing and Water supply related activities (see Figure 12).[14]

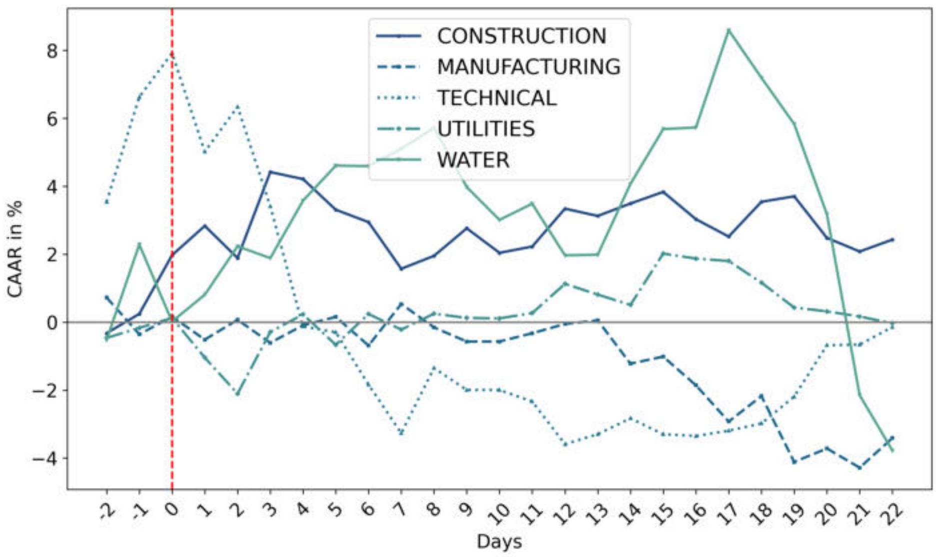
In Figure (13a) we report the results of the case study for the summer floods in norther Europe in summer 2021. After a breakdown by economic activity, we find that manufacturing or professional, scientific, and technical activities are negatively impacted by floods.

[14] Which are respectively section C,E and F of the NACE economic sections.



(a) Ciara

Figure 12. CAAR for Windstorm Ciara February 2020 by Industry: In Figure (12), we depict CAAR by NACE economic section breakdown for companies impacted by winter windstorm Ciara which formed on 10 February 2020 and dissipated on 16 February 2020. The Y-axis of each figure represents CAAR in %, and the X-axis days from the event, where positive values are after event beginning and negative before.

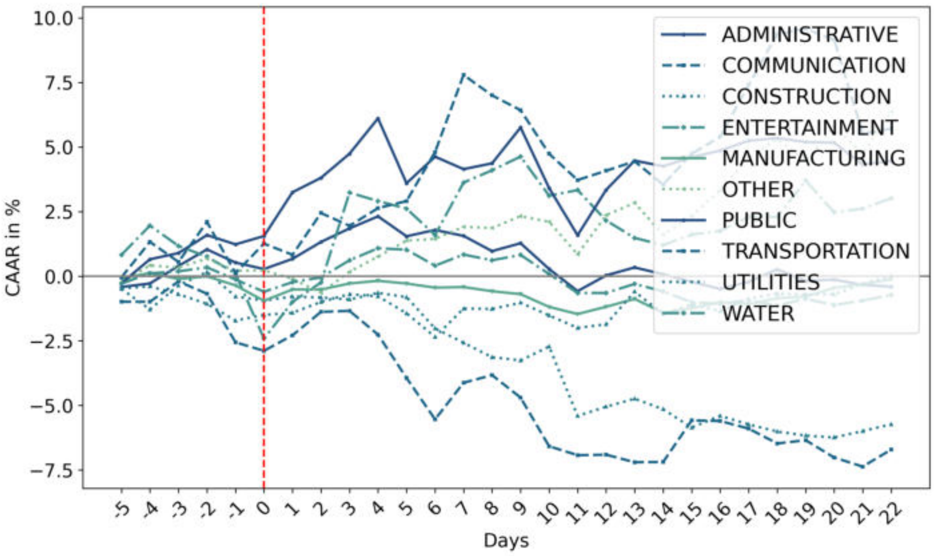


(a) Floods July 2021

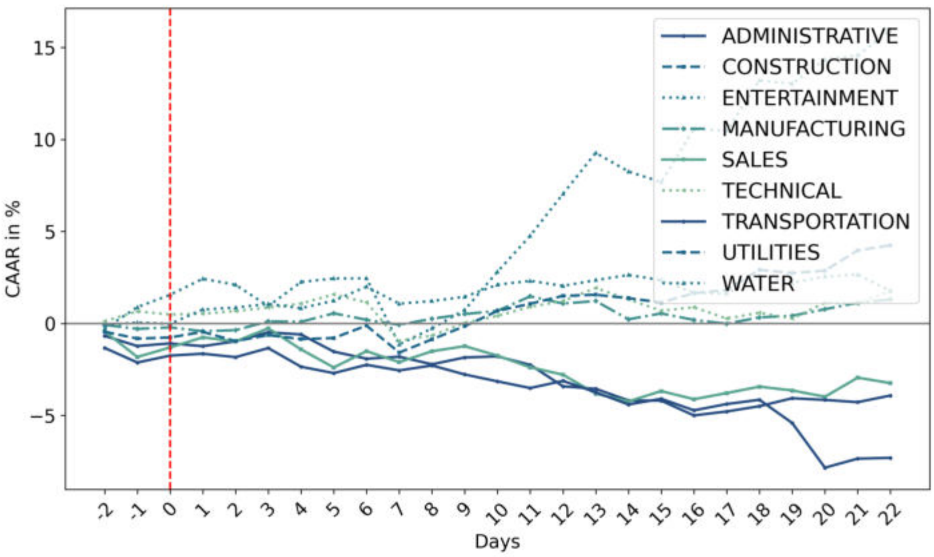
Figure 13. CAAR for the summer floods in Central Europe July 2021: In Figure (13) we compute CAAR by NACE economic section breakdown for companies impacted by the summer floods in Germany, Belgium and the Netherlands from 13 to 15 July 2021. The Y-axis of each figure represents CAAR in %, and the X-axis days from the event, where positive values are after event beginning and negative before.

H.a.1 The whole sample

Next we analyse whether the industry belonging of the company impacted plays a role for investors' reaction. In the specific we expect to see a stronger reaction for industry that have a material exposure to physical risks. For instance those highlighted in the (Dunz et al., 2021) , such as manufacturing and construction among others.



(a) Windstorms



(b) Floods

Figure 14. Cumulative Average Abnormal Returns (CAAR) by event type: In Sub-Figures (14a,14b) we depict CAAR by NACE economic section breakdown for companies impacted by winter windstorms and floods. The Y-axis of each figure represents CAAR in %, and the X-axis days from the event, where positive values are after event beginning and negative before.

Eyeballing Sub-Figures (14a) shows that the industries that are mostly impacted are manufacturing, utilities, construction and transportation.In Sub-Figures (14b) we see that transportation related activities seem to suffer most from floods.

I Replicating the analysis with other expected returns

	$CAR_{t,3F}$					
	WIND			FLOOD		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
β_0	0.4781**	0.4764**	0.6456***	0.1978	0.3258*	0.0563
	(0.1899)	(0.1910)	(0.2249)	(0.2224)	(0.1980)	(0.2377)
$LO_{(t-1)}$	0.0091***	0.0032	0.0061*	0.0022	-7.87e-05	0.0125***
	(0.0022)	(0.0034)	(0.0036)	(0.0027)	(0.0031)	(0.0036)
$Post$	-3.4715***	-2.8299***	-3.9193***	-0.5805**	-0.7356***	-0.7236***
	(0.2432)	(0.2644)	(0.2807)	(0.2664)	(0.2594)	(0.2755)
$LO_{(t-1)} \cdot Post$	0.0223***	0.0123***	0.0471***	0.0049	0.0083*	0.0011
	(0.0030)	(0.0050)	(0.0055)	(0.0038)	(0.0044)	(0.0047)
EAL_i		-50.768**			-0.0471	
		(25.178)			(0.0290)	
$LO_{(t-1)} \cdot EAL_i$		2.6674**			0.0012**	
		(1.3012)			(0.0005)	
$Post \cdot EAL_i$		-178.19***			0.0636*	
		(35.137)			(0.0351)	
$LO_{(t-1)} \cdot Post \cdot EAL_i$		4.2143***			-0.0021***	
		(1.4971)			(0.0007)	
$Dist$			-0.0001***			6.311e-05
			(3.98e-05)			(4.685e-05)
$LO_{(t-1)} \cdot Dist$			1.495e-06*			-2.737e-06***
			(7.849e-07)			(9.151e-07)
$Post \cdot Dist$			0.0001**			0.0001*
			(5.565e-05)			(6.491e-05)
$LO_{(t-1)} \cdot Post \cdot Dist$			-6.048e-06***			-2.11e-07
			(1.144e-06)			(1.338e-06)
N	5593	5593	5593	14022	14022	14022
R^2	0.0262	0.0476	0.0379	0.0018	0.0024	0.0051
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Table XI. Regression of $CAR_{it,3F}$ on LO_{t-1} and $EAL_i, Dist$: In Table (VII), we show fixed effects regression where $CAR_{it,3F}$ is dependent variable. The explanatory variables are: LO_{t-1} or the quarterly lagged percentage of home IO ownership calculated using the measure by Coeurdacier and Rey (2013), EAL_i or the expected annual loss. $Post$ which is a dummy equal 1 for the days at or after the event and $Dist$, which is the distance in kilometers between the facility and the headquarters as suggested in (Pellegrino et al., 2022). Covariance is clustered by time (Petersen, 2009).

	$CAR_{t,4F}$					
	WIND			FLOOD		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
β_0	0.1866	0.1769	0.3359	0.2267	0.3975	0.0489
	(0.2790)	(0.2856)	(0.2885)	(0.3105)	(0.2870)	(0.3229)
$LO_{(t-1)}$	0.0127***	0.0061*	0.0092***	0.0019	-0.0010	0.0124***
	(0.0018)	(0.0034)	(0.0035)	(0.0030)	(0.0035)	(0.0036)
$Post$	-2.9088***	-2.3284***	-3.3992***	-0.8324**	-1.0226***	-0.9816***
	(0.3431)	(0.3571)	(0.3577)	(0.3630)	(0.3574)	(0.3711)
$LO_{(t-1)} \cdot Post$	0.0199***	0.0116**	0.0466***	0.0039	0.0079	0.0004
	(0.0026)	(0.0045)	(0.0051)	(0.0046)	(0.0054)	(0.0046)
EAL_i		-48.049*			-0.0605*	
		(26.994)			(0.0313)	
$LO_{(t-1)} \cdot EAL_i$		2.9374**			0.0014***	
		(1.3805)			(0.0005)	
$Post \cdot EAL_i$		-156.54***			0.0757*	
		(36.378)			(0.0387)	
$LO_{(t-1)} \cdot Post \cdot EAL_i$		3.5388**			-0.0024***	
		(1.6036)			(0.0008)	
$Dist$			-0.0001***			9.801e-05
			(3.816e-05)			(6.422e-05)
$LO_{(t-1)} \cdot Dist$			1.468e-06*			-3.081e-06**
			(8.392e-07)			(1.204e-06)
$Post \cdot Dist$			0.0001***			0.0001
			(5.245e-05)			(8.245e-05)
$LO_{(t-1)} \cdot Post \cdot Dist$			-6.538e-06***			-2.69e-07
			(1.093e-06)			(1.654e-06)
N	5593	5593	5593	14022	14022	14022
R^2	0.0268	0.0428	0.0385	0.0012	0.0019	0.0047
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Table XII. Regression of $CAR_{it,4F}$ on LO_{t-1} and EAL_i, $Dist$: In Table (VII), we show fixed effects regression where $CAR_{it,4F}$ is dependent variable. The explanatory variables are: LO_{t-1} or the quarterly lagged percentage of home IO ownership calculated using the measure by Coeurdacier and Rey (2013), EAL_i or the expected annual loss. $Post$ which is a dummy equal 1 for the days at or after the event and $Dist$, which is the distance in kilometres between the facility and the headquarters as suggested in (Pellegrino et al., 2022). Covariance is clustered by time (Petersen, 2009).

	$CAR_{t,5F}$					
	WIND			FLOOD		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
β_0	0.5547***	0.5943***	0.6807***	0.0507	0.2030	-0.1390
	(0.1888)	(0.1963)	(0.2241)	(0.2138)	(0.1937)	(0.2297)
$LO_{(t-1)}$	0.0073***	-0.0013	0.0059*	0.0021	-0.0003	0.0129***
	(0.0027)	(0.0034)	(0.0032)	(0.0029)	(0.0033)	(0.0033)
$Post$	-3.4155***	-2.7196***	-3.6561***	-0.3670	-0.4652*	-0.5086*
	(0.2403)	(0.2667)	(0.2790)	(0.2577)	(0.2541)	(0.2666)
$LO_{(t-1)} \cdot Post$	0.0219***	0.0108**	0.0455***	0.0016	0.0040	-0.0018
	(0.0036)	(0.0051)	(0.0049)	(0.0043)	(0.0048)	(0.0043)
EAL_i		-82.728***			-0.0522*	
		(22.728)			(0.0281)	
$LO_{(t-1)} \cdot EAL_i$		3.8640***			0.0011**	
		(1.1432)			(0.0005)	
$Post \cdot EAL_i$		-181.06***			0.0419	
		(31.492)			(0.0338)	
$LO_{(t-1)} \cdot Post \cdot EAL_i$		4.7448***			-0.0017**	
		(1.3459)			(0.0007)	
$Dist$			-9.816e-05**			0.0001**
			(4.959e-05)			(4.556e-05)
$LO_{(t-1)} \cdot Dist$			9.983e-07			-3.204e-06***
			(7.558e-07)			(8.701e-07)
$Post \cdot Dist$			-1.327e-05			0.0001*
			(6.817e-05)			(6.492e-05)
$LO_{(t-1)} \cdot Post \cdot Dist$			-4.704e-06***			-2.249e-07
			(1.214e-06)			(1.314e-06)
N	5593	5593	5593	14022	14022	14022
R^2	0.0220	0.0475	0.0396	0.0005	0.0013	0.0047
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Table XIII. Regression of $CAR_{it,5F}$ on LO_{t-1} and $EAL_i, Dist$: In Table (VII), we show fixed effects regression where $CAR_{it,5F}$ is dependent variable. The explanatory variables are: LO_{t-1} or the quarterly lagged percentage of home IO ownership calculated using the measure by Coeurdacier and Rey (2013), EAL_i or the expected annual loss. $Post$ which is a dummy equal 1 for the days at or after the event and $Dist$, which is the distance in degrees between the facility and the headquarters as suggested in (Pellegrino et al., 2022). Covariance is clustered by time (Petersen, 2009).

J Robustenss tests: excluding the US and year 2020

	$CAR_{t,Mkt}$ w/o the United States					
	WIND			FLOOD		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
β_0	-0.5332	-0.5538*	-0.4216	0.1966	0.2437	0.1618
	(0.3504)	(0.3323)	(0.3757)	(0.2366)	(0.2313)	(0.2436)
$LO_{(t-1)}$	0.0153***	0.0145***	0.0164***	0.0076**	0.0068*	0.0113***
	(0.0032)	(0.0043)	(0.0039)	(0.0033)	(0.0037)	(0.0036)
$Post$	-2.4516***	-1.8738***	-2.7300***	-0.7985***	-0.9432***	-0.8671***
	(0.4492)	(0.4545)	(0.4790)	(0.2863)	(0.2928)	(0.2937)
$LO_{(t-1)} \cdot Post$	0.0366***	0.0233***	0.0504***	0.0074*	0.0131**	0.0053
	(0.0041)	(0.0052)	(0.0053)	(0.0044)	(0.0051)	(0.0048)
EAL_i		-0.0977			-0.0148	
		(20.473)			(0.0314)	
$LO_{(t-1)} \cdot EAL_i$		0.4867			0.0003	
		(1.0974)			(0.0007)	
$Post \cdot EAL_i$		-200.44***			0.0729**	
		(34.537)			(0.0369)	
$LO_{(t-1)} \cdot Post \cdot EAL_i$		5.5407***			-0.0039***	
		(1.3211)			(0.0009)	
$Dist$			-5.052e-05			4.938e-05
			(5.927e-05)			(6.296e-05)
$LO_{(t-1)} \cdot Dist$			-1.181e-06			-3.402e-06**
			(1.233e-06)			(1.335e-06)
$Post \cdot Dist$			0.0003***			4.606e-05
			(8.504e-05)			(7.746e-05)
$LO_{(t-1)} \cdot Post \cdot Dist$			-1.268e-05***			1.723e-06
			(2.128e-06)			(1.763e-06)
N	4557	4557	4557	12270	12270	12270
R^2	0.0406	0.0582	0.0582	0.0048	0.0097	0.0056
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Table XIV. Regression of $CAR_{it,Mkt}$ on LO_{t-1} and $EAL_i, EAL_{it,UN}, Dist$: In Table (VII), we show fixed effects regression where $CAR_{it,5F}$ is dependent variable. The explanatory variables are: LO_{t-1} or the quarterly lagged percentage of home IO ownership calculated using the measure by Coeurdacier and Rey (2013), EAL_{ii} or the expected annual loss without accounting for the country insurance gap, and $EAL_{i,UN}$ accounting for the insurance gap in the country. $Post$ which is a dummy equal 1 for the days at or after the event and $Dist$, which is the in degrees between the facility and the headquarters as suggested in (Pellegrino et al., 2022). Covariance is clustered by time.

	$CAR_{t,Mkt}$ the year 2020					
	WIND			FLOOD		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
β_0	-0.0140	0.0640	0.1748	0.3353	0.3892*	0.2416
	(0.2785)	(0.3549)	(0.2828)	(0.2364)	(0.2255)	(0.2546)
$LO_{(t-1)}$	0.0116***	-0.0069	0.0067	0.0019	0.0005	0.0093***
	(0.0022)	(0.0049)	(0.0053)	(0.0027)	(0.0031)	(0.0036)
$Post$	-2.1879***	-2.5233***	-2.6932***	-0.6651**	-0.7862***	-0.8537***
	(0.3457)	(0.5205)	(0.3543)	(0.2856)	(0.2890)	(0.3055)
$LO_{(t-1)} \cdot Post$	0.0203***	0.0330***	0.0493***	0.0029	0.0058	0.0043
	(0.0032)	(0.0074)	(0.0068)	(0.0038)	(0.0045)	(0.0049)
EAL_i		-240.65**			-0.0240	
		(102.94)			(0.0297)	
$LO_{(t-1)} \cdot EAL_i$		9.0990***			0.0008	
		(1.7440)			(0.0005)	
$Post \cdot EAL_i$		469.44***			0.0528	
		(173.79)			(0.0351)	
$LO_{(t-1)} \cdot Post \cdot EAL_i$		-7.0239***			-0.0018**	
		(2.4778)			(0.0007)	
$Dist$			-0.0001**			2.793e-05
			(4.659e-05)			(4.979e-05)
$LO_{(t-1)} \cdot Dist$			1.716e-06			-1.791e-06**
			(1.137e-06)			(8.678e-07)
$Post \cdot Dist$			0.0001			0.0001**
			(6.817e-05)			(6.509e-05)
$LO_{(t-1)} \cdot Post \cdot Dist$			-6.017e-06***			-1.411e-06
			(1.537e-06)			(1.168e-06)
N	4445	4445	4445	13615	13615	13615
R^2	0.0313	0.0430	0.0460	0.0010	0.0016	0.0038
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Table XV. Regression of $CAR_{it,Mkt}$ on LO_{t-1} and $EAL_i, EAL_{it,UN}, Dist$: In Table (VII), we show fixed effects regression where $CAR_{it,5F}$ is dependent variable. The explanatory variables are: LO_{t-1} or the quarterly lagged percentage of home IO ownership calculated using the measure by Coeurdacier and Rey (2013), EAL_{ii} or the expected annual loss without accounting for the country insurance gap, and $EAL_{i,UN}$ accounting for the insurance gap in the country. $Post$ which is a dummy equal 1 for the days at or after the event and $Dist$, which is the distance in degrees between the facility and the headquarters as suggested in (Pellegrino et al., 2022). Covariance is clustered by time.