EUROPEAN CENTRAL BANK

EUROSYSTEM

Working Paper Series

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Local institutional ownership and price discovery around extreme weather events

No 3069

Abstract

In this event study, we analyze the effect of market segmentation on stock returns in Europe amid extreme weather events. We show that local institutional ownership (LIO) mitigates the negative effect of the uncertainty from the occurrence of extreme weather events on stock prices. We assess firms' exposure to physical climate risks using the Eurosystem's method that uses physical climate risk indicators. In a sample with materially exposed industries, we find a negative risk-adjusted abnormal return of 99 basis points for storms on the event date. This negative return is mitigated however by 1.3% for each percentage point increase in LIO. We confirm the mitigating role of LIO by testing the information hypothesis through two channels: the distance between a firm's headquarters and the affected facility and its exposure to physical risk.

JEL: C81, G11, G14, G32, Q54

Keywords: extreme weather events, event study, asset pricing, market segmentation

Non-technical summary

Financial asssets are increasingly exposed to climate risks, yet investor reactions to extreme weather events remain uncertain. This study explores how local institutional ownership (LIO) influences stock price movements during extreme weather events in Europe. We find that LIO plays a stabilizing role, helping to mitigate the negative impact of storms and floods on stock returns. Using data from 2014 to 2022, we analyze publicly listed firms with varying levels of LIO and assess their exposure to physical climate risks through the Eurosystem's methodology.

Our findings reveal that extreme weather events, particularly storms, lead to significant declines in stock prices. On average, stocks of affected companies experience a negative abnormal return of 99 basis points on the event date. However, this negative effect is reduced by 1.3 percentage points for each additional percentage point of LIO. This suggests that local institutional investors, who are more familiar with companies' exposure to climate risks, incorporate this knowledge into their investment decisions. As a result, firms with higher LIO experience less pronounced price drops, as the risks are already reflected in stock valuations before the event occurs.

Furthermore, our study highlights the importance of geographic proximity in mitigating uncertainty. When a company's affected facility is located farther from its headquarters, stock price reactions tend to be stronger. This indicates that informational distance plays a crucial role in investors' ability to assess climate-related risks. Local institutional investors, who often have better access to firm-specific information, are more effective in stabilizing stock prices when the affected assets are geographically closer.

Interestingly, we also find a difference in how investors respond to different types of extreme weather events. While stock prices tend to react negatively to storms, the response to floods is more mixed and depends on the severity of the event. A potential explanation lies in the nature of the events and the predictability of their impact. According to Merz et al. (2020), the main uncertainty in storm forecasting concerns the storm track and the extent of its impact. Storms can potentially affect large areas, making their consequences harder to predict. In contrast, floods, although often severe, tend to be more geographically localized and can be anticipated with greater accuracy. This is especially true when information such as flood risk maps and the likelihood of government intervention is available in advance. However, the final impact of floods still depends on complex local conditions.

Our methodology combines financial market data, institutional ownership records, and detailed climate risk assessments. We use facility-level data from the European Pollutant Release and Transfer Register (E-PRTR) and company ownership data from Amadeus to link firms to their physical assets. Additionally, we estimate expected annual losses due to extreme weather events using the Eurosystem's framework, which incorporates land use, historical weather patterns, and facility-specific exposure. By applying event study techniques, we measure abnormal stock returns before and after extreme weather events, allowing us to quantify investor reactions.

These findings have important implications for both investors and policymakers. For financial institutions, understanding the role of LIO can improve portfolio risk management and investment strategies in the face of climate-related uncertainty. Our results suggest that companies with a strong base of local institutional investors may be less vulnerable to abrupt price declines following extreme weather events. For regulators and policymakers, enhancing transparency in climate risk disclosures and making facility-level climate exposure data more accessible could help improve market efficiency.

Introduction

Market segmentation and extreme climate events challenge price discovery in financial markets. Regulatory barriers, transaction costs, information asymmetry, and geographic limitations restrict certain investors from fully participating in the market. Consequently, distinct investor groups may interpret or react to information differently that potentially leads to price inefficiencies. Segmented markets may therefore fail to fully reflect the relevant risks for asset prices, undermining overall market efficiency. Extreme weather events related to climate change provide a compelling context to test the effects of market segmentation on asset prices.

The World Economic Forum highlights extreme weather events and information barriers as major threats to global economies (WEF, 2024). Since 1980, extreme weather has globally caused $3 trillion in losses that is expected to grow with rising temperatures. Information barriers are also likely to increase due to de-globalization, further constraining investment decisions (Basel Committee on Banking Supervision, 2021; Pellegrino et al., 2024).[1] The extreme weather events and the rising information barriers will exacerbate market segmentation as they will affect asset returns through heightened uncertainty.

Studies have well established that extreme weather events increase uncertainty in stock returns. This effect is especially pronounced when investors are not fully diversified due to segmented markets or when behavioral biases, such as the salience of these events, influence investment decisions (Alok et al., 2020; Kruttli et al., 2025). To reduce uncertainty, investors tend to focus on stocks they are more familiar with, often based on geographical proximity, or on stocks where they have a comparative advantage (Coval and Moskowitz, 1999, 2001; Van Nieuwerburgh and Veldkamp, 2009).

In this study, we investigate how information asymmetries among market participants that are influenced by ownership structure and physical distance affect the equity price discovery during extreme weather events. Specifically, we examine whether local institutional ownership (LIO) mitigates the negative effects of uncertainty on stock prices in these contexts. Using extreme weather events as a natural experiment, we analyze the price discovery of publicly listed companies with varying levels of LIO. We test two mechanisms to demonstrate that local investors possess greater knowledge about companies' exposure to such events: (1) those with higher expected annual losses from an extreme weather event but greater LIO should experience smaller

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

negative price surprises, as it has already priced the potential loss, and (2) the farther a facility is from the headquarters of the company, the weaker the informational advantage of LIO. We define a company's headquarters as the country from which it issues its stock.

To address the research question, we focus on Europe, a region historically exposed to market segmentation and increasingly affected by extreme weather events (Boermans and Galema, 2025).[2] We use data and methods from European institutions (EIOPA, 2022; Statistics Committee of the ESCB, 2023) to identify the companies affected by extreme weather events by overlaying event areas with facility locations from the European Pollutant Release and Transfer Register (E-PRTR).[3] We record storm data from the European Commission *Climate Data Store (Copernicus)* and flood areas, timing, and intensity from the Dartmouth Flood Observatory (DFO) (Brakenridge, 2025). A high-performing name-matching algorithm links facility ownership data from the E-PRTR with the company ownership structures in Amadeus, a database on European private and public companies, thus associating facilities with their publicly listed parent companies. Using FactSet data, we then calculate risk-adjusted cumulative abnormal returns (CAR) around the event.

Due to our innovative data sources and geographic focus, we first validate our approach using a case study before applying an event study to the full sample. Specifically, we analyze two case studies: the February 2020 Storm Ciara that started in Ireland and Great Britain (GB) and the July 2021 river floods in Germany, Belgium, and the Netherlands.[4] Next, we implement a standard event study for all extreme weather events from 2014 to 2022 by following the established guidelines (MacKinlay, 1997; Barrot and Sauvagnat, 2016; Barnett, 2024). To compute the abnormal returns, we use the 3- and 5-factor Fama-French models as well as the 4-factor Carhart model (Fama and French, 1993; Carhart, 1997; Fama and French, 2015). We test for any significant deviations in the actual returns from the predicted returns using the robust cross-sectional variance method adjusted for event-induced variance by Boehmer et al. (1991). Next, we assess the effect of LIO on the cumulative abnormal returns (CAR) through panel regressions.

In our analysis, we hypothesize that foreign investors do not have the same level of access

[2] For more information on climate change effects in Europe, see Fragile State Index (FSI) and (Kemp et al., 2022).

[3] An overlay estimates the attributes of features by superimposing them over other features and measuring the extent of overlap. This practice, known as *spatial finance*, enhances transparency and accountability (McCarten et al., 2021; Patterson et al., 2022).

[4] The storm was selected based on its impact by the European Insurance and Occupational Pensions Authority (EIOPA). The July 2021 floods caused approximately 50 billion in economic damage, as reported in the 8th EAP.

to information as local investors; this is a concept known as the "information hypothesis". This disparity arises for several reasons: local investors may have a comparative advantage in information about local stocks, actively disregard signals from foreign stocks, or face high costs of obtaining information about distant stocks (Klein and Bawa, 1977; Merton, 1987; Pellegrino et al., 2024). We expect this assumption to hold especially for extreme weather events because they are still an under-explored risk for investors due to their novel, complex, localized effects, and the challenges in accurately predicting their financial consequences.

We make four key findings: (i) Consistent with the literature, we find that investors typically react negatively to storms, but their responses to floods are mixed and model-dependent (Alok et al., 2020; Huynh and Xia, 2021; Kruttli et al., 2025). The forecasts of storms have longer horizons and higher uncertainty compared to those for floods, resulting in stronger reactions (Merz et al., 2021). Additionally, investors are less reactive to flood risks, likely because government interventions in rebuilding flood-prone areas have reduced their concerns about them (Alok et al., 2020; Giglio et al., 2025). (ii) The negative effect of storms on stock returns is mitigated by 1.3% for each percentage point increase in LIO. This result is both economically and statistically significant and aligns with the information hypothesis (Coval and Moskowitz, 2001; Van Nieuwerburgh and Veldkamp, 2009; Giannetti and Laeven, 2016). (iii)We find that by interacting LIO with companies' exposures to storms mitigates the negative reactions of investors. This is because local investors are likely to have already priced in the higher risk exposure and therefore are less surprised by the occurrence of the event. (iv) However, the negative investor reaction intensifies when we interact LIO with the distance between the company's headquarters and the affected area. This finding also supports the information hypothesis by showing that greater informational distance amplifies the reaction.

Given the limited sample size for the time series, we face two main challenges in implementing the empirical setting of our event study: limited access to information on companies' physical assets and the difficulty of translating economic losses into financial losses and price shocks. To address the first challenge, we use the E-PRTR register to identify the location of production facilities. To address the second challenge, we estimate the counterfactual – or expected returns – during the event by using a 90-day estimation window of daily returns that excludes weather-related disaster events for each company and each event. This approach aligns closely with the 120-day estimation period used by Kruttli et al. (2025), although our method is more conservative in terms of timing than Blanco et al. (2024). We also limit our sample to stocks priced above €

5 during the estimation period and with at least a 10% free float, which is a similar practice to other studies (Barnett et al., 2021).

Our work contributes to the understanding of market segmentation and investors' perspectives on climate risks by addressing key questions in climate finance (Starks, 2023). Specifically, we contribute to two main streams of literature. First, we add to the research on the effect of securities' ownership on investors' reactions to shocks by examining how local and non-local ownership dynamics unfold in a region characterized by strong home bias. For instance, Huynh and Xia (2021) show that investors tend to overreact by depressing prices after natural disasters, leading to higher future expected returns for the affected securities. Furthermore, the authors show that insider trading behavior helps revert prices when they fall below fundamental value, and that long-term, sustainability-oriented institutional investors have a positive impact on prices following such events. Blanco et al. (2024) demonstrate that institutional investors with significant portfolio exposure to natural disasters divest from disaster-affected stocks while reducing trading intensity in unaffected stocks, thus ending with portfolio holdings that predict lower medium-term returns. However, the authors focuse on the impact of ownership changes on trading patterns and returns, without addressing the role of local versus non-local ownership dynamics in explaining return behavior. Additionally, Glossner et al. (2025) examine how security ownership influences price pressures after the Covid-19 pandemic. We extend this literature by investigating the role of local institutional ownership in mitigating the negative effect of extreme weather events on stock prices. Specifically, we explore two mechanisms: the distance between the facilities and headquarters of companies, and the exposure to expected annual losses from extreme weather events. Our empirical findings contribute to the literature by demonstrating how local informational advantages mitigate the uncertainty driven by extreme weather events under market segmentation.

Second, we contribute to the literature with examinations of the effect of extreme weather events on asset prices using innovative data sources (Alok et al., 2020; Huynh and Xia, 2021; Bressan et al., 2024; Kruttli et al., 2025; Blanco et al., 2024). Specifically, we leverage the information contained in European pollutant release and transfer registers (E-PRTR) to identify the affected facilities. This study contributes to the ongoing debate about the necessity of making climate data publicly available to enhance replicability and transparency in climate finance (Condon, 2023). The use of publicly available non-financial data has proven effective for financial forecasting (Dessaint et al., 2024). For example, data on parking lot traffic has helped explain performance differences between quantitative asset managers and those relying on traditional stock-picking based on industry expertise (Bonelli and Foucault, 2023).[5] We contribute to this line of research by incorporating atmospheric data related to climatic events such as storms and floods.

Our findings hold relevance for both European institutions and finance practitioners. For instance, improvements to the E-PRTR could enhance its utility for financial analysis by adding data on the facilities' workforce, financial value, and the extent of existing adaptation measures. Such enhancements would enable more accurate damage assessments and more comprehensive financial evaluations. Regarding the data on extreme weather events provided by Copernicus, while the geographic coverage is precise, there are notable gaps, particularly the absence of data on lower intensity storms for 2018 and 2019, as well as missing information on tropical Mediterranean storms that is an issue that gained importance following the sinking of the *Bayesian* yacht in the Mediterranean Sea or the DANA in Spain in October 2024. For practitioners, our study demonstrates the value of developing alternative data sources independent of traditional ESG rating providers. In particular location data can also be applied to research on biodiversity risks that further expand their relevance for sustainable finance.

We structure the paper as follows: In Section I, we introduce the theory that motivates our empirical analysis; and in Section II, we formulate our research hypotheses. Section III presents the empirical setting and physical risk scores, followed by Section IV, where we introduce the data sources and the sample. We then continue with two case studies in Section IV to validate our method. In Section VI, we present the results for the full sample, addressing the hypotheses formulated earlier. Finally, we conclude in Section VIII.

I Motivating theory

Market segmentation refers to the division of investors into distinct groups based on factors such as geographical location, cultural differences, and access to information. This phenomenon can have two main consequences: pricing inefficiencies and under-diversified portfolios.

Pricing inefficiencies refer to situations where asset prices deviate from their fundamental values due to market imperfections or frictions. In the context of market segmentation, these

[5] An example is RS Metrics' historical data on store-level parking lot traffic, including collection start dates for 48 publicly listed U.S. retailers (Bonelli and Foucault, 2023).

inefficiencies arise because different groups of investors may have limited access to information, different levels of familiarity with the assets, or restrictions on where they can invest. As a result, prices may not fully reflect all available information that leads to mispricing. This mispricing means that securities could be overvalued or undervalued, affecting the optimal allocation of capital in the real economy via financial markets.

Pricing inefficiencies in global financial markets can arise from the high cost of accessing information across borders. In a quantitative theory model of international capital allocation by Pellegrino et al. (2024), investors form expectations about the destination country using both free and costly signals, with the latter reducing their utility. Acquiring such signals is more efficient in countries that are geographically, culturally, and linguistically closer. Consequently, when information is less precise—particularly with respect to the destination country—a change in stock price results in a smaller shift in the demand curve, reflecting lower demand elasticity. Investors are reluctant to acquire costly signals unless they significantly improve their understanding that results in less elasticity in demand when information is more distant or difficult to obtain. Given the complexity, uncertainty, and need for specialized—often local—expertise, we conjecture that information on firms' exposure to climate-related risks is particularly costly. [6]

Market segmentation may also lead to under-diversified portfolios that can exacerbate the effect of idiosyncratic shocks on asset prices. As argued by Merton (1987), investors tend to invest in securities they are familiar with, resulting in under-diversification where shocks to idiosyncratic volatility can affect expected returns.

We derive a model from Merton (1987) and Kruttli et al. (2025) to show how extreme weather events effect the expected stock returns in a segmented market (See Appendix A for more detail). This model demonstrates that climate-related shocks affect expected returns when investors face segmented markets. This result is in contrast to the standard CAPM framework in which market segmentation does not exist and where idiosyncratic shocks are diversified away so as to not have any effect on expected returns (Strobl, 2011). The theoretical framework accounts for two main types of uncertainty caused by extreme weather events that affect stock returns: *incidence uncertainty* and *impact uncertainty*. Incidence uncertainty refers to the unpredictability of whether a company will be hit by an extreme weather event, while impact uncertainty reflects the degree to which the company will be affected if hit.

[6] Several papers have noted that investors achieve higher returns when they invest locally (Coval and Moskowitz, 1999, 2001; Van Nieuwerburgh and Veldkamp, 2009; Giannetti and Laeven, 2016).

Intuitively, the expected return of a stock reflects the risk-free rate, its correlation with the broader financial market, and an additional variance component driven by stock-specific factors. In the model developed by Merton (1987) and extended by Kruttli et al. (2025), this variance depends on the number of investors aware of the stock's existence and its market share. When information asymmetry is present, expected returns increase with higher variance, which arises either from lower investor awareness leading to less due diligence or from a higher market share combined with elevated risk aversion. We further decompose the variance into three components: an idiosyncratic element and two related to extreme weather events. The first, *incidence uncertainty*, captures the probability that a company is affected by such an event. The second, *impact uncertainty*, reflects uncertainty about the severity of the event's effect on the firm. Both contribute to higher expected returns; however, impact uncertainty only affects returns prior to the realization of the extreme weather event.

II Hypotheses

Building on the theoretical considerations introduced in Section (I), we hypothesize that stock prices can be influenced by both idiosyncratic extreme weather events and investors' knowledge of a company's risk exposure, which we assume is higher for local institutional investors. To empirically test these relations we formulate four hypotheses in this section.

First, we test the effect of different types of weather events on stock prices. The literature has shown that the incidence and effect of storms are less predictable compared to floods (Merz et al., 2020). We provide a practical example of early warning systems for storms and floods in Appendix B. For Hurricane Ian on September 2022 in the US, we demonstrate that the precision of incidence predictions improved over the span of a few days. In contrast, for the floods in Germany in June 2024, we show that prediction certainty was higher from the outset. Floods represent a more contained setting, as the locations of rivers and weak spots are known in advance. Based on these differences between storms and floods, we hypothesize that:

H_1: *The securities of firms that are affected by more predictable events experience less negative cumulative average abnormal returns (CAAR) compared to those affected by less predictable ones.*

Second, we test what the effect of LIO, or the share of investors who are informed about the company, is on stock prices under distress. In Section (I), we saw that local investors have an informational advantage over other investors when signals are costly. Therefore, we expect companies with a greater average presence of LIO to experience a smaller negative surprise from extreme weather events. This expectation is plausible for two reasons: first, local investors tend to do more thorough due diligence on local companies, thereby reducing informational distance (Coval and Moskowitz, 1999, 2001; Van Nieuwerburgh and Veldkamp, 2009); second, the share elasticity is higher for local investments. Local investors are more likely to demand a higher quantity of shares for a smaller price decline if they anticipate higher returns, which helps mitigate the negative price effect (Pellegrino et al., 2024). As a result, the demand for these companies' shares will adjust more quickly to an increase in supply compared to companies whose shares are predominantly held by foreign investors. This difference leads to our second hypothesis:

H_2: *The greater the degree of local institutional ownership in a security before an event, the higher the cumulative abnormal returns (CAR) will be around the event's occurrence.*

Third, we test the effect of local institutional ownership on stock prices when facilities are located in regions with higher exposure to extreme weather events. This effect provides insight into local institutional investors' ability to assess a company's exposure to weather-related risks. We expect local investors to have a deeper understanding of the company's vulnerabilities to such events. Specifically, the interaction between local ownership and expected annual losses from extreme weather events should positively affect the security's performance on the event date. To test this information channel, we formulate the third hypothesis as follows:

H_3: *The positive effect of local institutional ownership is larger when the affected facilities are located in regions with higher exposure to extreme weather events.*

Fourth, we test the effect of physical distance as a proxy for informational distance by measuring the distance between a company's headquarters and the affected facility. We hypothesize that greater physical or informational distance reduces the precision of investors' information. Consequently, when a facility is located further from the company's headquarters, investors will have less knowledge of the affected physical assets. Therefore, the greater the distance between a firm's facilities and its headquarters, the weaker the positive effect of local ownership on securities' performance. This is logical, as companies rarely disclose their exposure to extreme weather events at the facility level, making it more costly for investors to access this information. We test this second channel by formulating the fourth hypothesis as follows:

H_4: *The positive effect of local institutional ownership weakens as the distance between a facility and the company's headquarters increases.*

III The empirical setting and physical risk scores

To address these hypotheses, we link facilities to their parent companies using a name matching algorithm, quantify the proportion of LIO in these parent companies, and extract geographic data on the occurrence of extreme weather events. Using this information, we introduce the event study in which we analyze the effect of these extreme weather events on securities prices and investor behavior.

III.a The name matching algorithm: linking facilities with parent companies

The first step is to link facilities to their parent companies using a name matching algorithm. We retrieve the names for facility ownership from the E-PRTR and company names from Amadeus, a Bureau van Dijk product. We calculate multiple string similarity measures and then test several machine learning algorithms to leverage these measures' strengths for accurate name matching.[7]

To streamline the matching process, we preprocess the company names from both the facility owners' sample (E-PRTR) and the sample of company names (Amadeus). We normalize these names with the following steps: First, we convert all characters to lowercase. Second, we compile a comprehensive list of commonly occurring suffixes across European languages. For instance, "International" is abbreviated to "#INT" to reduce computational complexity. Third, we compute the cosine similarity of the strings, defined as the cosine of the angle between two non-zero vectors in a multidimensional space, and retain only those with a similarity score above 60% to get a list of paired names.

After this preprocessing, we compute the string similarity measures with complementary strengths for the list of paired names. Specifically, we calculate Jaro-Winkler, Levenshtein, and Q-gram similarities between every retained name match from the sample of facility owners and the sample of company names (van der Loo, 2014). These measures are complementary: Jaro-Winkler focuses on prefix similarity, Levenshtein on the edit distance between two strings, and Q-gram is effective at identifying localized differences. While character-based measures like Levenshtein and Jaro-Winkler handle typographical errors well, they struggle with capturing similarities when the order of characters changes that is where the Q-gram measure excels (Gali et al., 2019).

[7] The algorithm is developed by Michiel Nijhuis from the Data Science Hub of De Nederlandsche Bank. See this webpage for more information: Company Name Matching.

After computing the string similarity measures, we use the resulting scores as input variables for various machine learning classification algorithms, testing their classification accuracy on a manually labeled sample. To match facility owners with company names, we create a balanced sample of 2,400 randomly selected entries that we manually classify to evaluate the performance of different machine learning (ML) algorithms in combining the string similarity measures. To prevent overfitting, we split the sample into training and test sets through cross-validation. The results of this analysis are presented in Table (I). It shows the average and variation of several performance measures assessing the classification quality of the implemented supervised ML methods.

We choose the "Extra Tree" (ET) method to classify the matches. To determine which supervised machine learning algorithm performs best, we use a set of performance measures. For cross-validation, we divide the sample into six parts and test the algorithm 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 ET classification method shows the highest accuracy ratio and very high levels of precision and recall and a rate of 89% of true positives. Although some measures outperform ET in terms of average values, ET retains the lowest standard deviation (σ) for most measures. Additionally, our decision is supported by an Area Under the Curve (AUC) analysis, provided in Appendix (C).

After running the ET on the full sample of potential matches, we link each facility to the first publicly listed entity in its ownership structure. Specifically, we identify the first publicly listed company in the historical ownership chain of the facility owner. Amadeus provides information on subsidiaries; immediate shareholders (ISH), the immediate majority security owner of the company; domestic ultimate owners (DUO), the majority security owner within the same country; and global ultimate owners (GUO), the last global majority owner of the company's securities. Each of these ownership tiers is based on an ownership chain of at least 50%. To select which stock to link with the facility, we first consider the subsidiary, then the owner of the subsidiary, followed by ISH, DUO, and GUO.

III.b Measuring securities' local institutional ownership

The second step is to calculate the LIO of stocks by aggregating the investments of all LIO in a local company. Local means that the institutional owner and the company are based in the same

		SVM	Logit	Tree	NB	AB	GB	RF	ET	KNN
Accuracy	μ	56	73	86	71	80	87	88	88	84
	σ	7	10	3	7	9	5	4	3	5
F1	μ	36	72	85	74	78	87	88	87	84
	σ	36	15	4	9	14	6	5	4	6
Precision	μ	45	69	88	65	81	89	90	89	84
	σ	35	6	4	4	3	3	4	3	2
Recall	μ	49	79	83	88	78	85	85	86	85
	σ	49	23	7	16	21	9	7	7	10

Table I. Supervised machine learning algorithms by classification performance: Table (I) presents 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), decision tree (Tree), naive Bayes (NB), adaboost (AB), gradient boost (GB), random forest (RF), extra tree (ET), and k-nearest neighbor (KNN) classification models. The 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.

country. Inspired by Coval and Moskowitz (2001) and Coeurdacier and Rey (2013), we define LIO in company i at time t as follows:

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

We use this LIO measure as a proxy for the general preference level of local investors for local companies. Following the approach of Boermans and Galema (2025), we collect all institutional owners of the companies in the sample and classify them as local if their country of residence matches that of the company's. We determine the location of a company's headquarters to classify the issued security as either local or non-local, as managers base investment decisions on the securities available in the market rather than the geographical distribution of a company's physical assets (Coval and Moskowitz, 1999).

III.c Expected annual loss (EAL): the Eurosystem method

In the third step, we calculate the physical risk indicators in the form of expected annual losses (EAL) at the company level by using the framework developed by the Eurosystem of Central

Banks (Statistics Committee of the ESCB, 2023).[8] This approach offers several advantages. First, it allows us to compute expected losses at the facility level that we then aggregate to determine the average EAL at the company level. Second, it eliminates reliance on third-party methods that may be less transparent or could become unavailable over time (Condon, 2023). We begin with explaining the reasoning behind our method followed by an exact explanation.

We replicate the framework from Statistics Committee of the ESCB (2023) to compute the company-level EAL by using data on facility locations, land use, extreme weather events, building-type distribution maps, and damage functions, as shown in Figure 1. Facility location data are sourced from the E-PRTR (mid-left panel of Figure 1), while land use maps are provided by Copernicus Land Monitoring (upper left panel of Figure 1). Land use refers to the management and designation of land for specific activities, such as residential, commercial, agricultural, industrial, and recreational purposes.

To compute the EAL from extreme weather events at a facility level, we follow three main steps. First, we calculate the probabilities of events with specific intensities occurring at the facility's location. Second, we identify the damage functions associated with these intensities to estimate the losses incurred by the facility. Third, we compute the EAL as the weighted average of probabilities and losses for all potential events that could affect the facility's location. In the following paragraphs, we detail these steps for storms and floods, using the visualization on storms from Figure 1 to guide understanding.

To compute the EAL from storms at a facility level, we first calculate the probability of an event with a given intensity occurring in the facility's location within the next year. To achieve this, we use maps of extreme weather event intensities based on historical occurrences for storms (lower left panel of Figure 1). Specifically, we use historical footprint maps of European storms since 1980 that come in a pixel format with a grid size of 1 km. For each pixel, we derive a distribution of wind intensity recordings based on observations from 1980 onward. Return periods or the probabilities of a storm occurring within a given wind intensity range in a year are computed by fitting the historical distribution of events at each geographic pixel to a Gumbel distribution (lower middle panel of Figure 1).[9] In the second step, we identify the level of damage a facility would incur from an event with a specific wind intensity. To do this identification, we

[8] The framework introduced by Statistics Committee of the ESCB (2023) refers to Antofie et al. (2020) to explain the calculations in detail.

[9] The Gumbel distribution is commonly used to model the distribution of the maximum (or minimum) of a number of samples from various distributions. For example, in this context, it represents the distribution of maximum wind intensity in a specific region.

require the building type of the facility, the wind intensity of the event, and the associated loss. Since the E-PRTR does not provide information on the facility's building type, we use a proxy suggested by Statistics Committee of the ESCB (2023): the combination of land use and the distribution of buildings by land use for each country in Europe. In other words, the building type of the facility is approximated as the weighted average of building types for the corresponding land use and is based on the frequency of buildings in that area (Jaiswal et al., 2010).[10] Now, the damage functions for Europe are calibrated for different types of buildings by Feuerstein et al. (2011). An example for this step is provided in the upper middle panel of Figure 1. Consequently, the damage functions for storms at the facility level result from the weighted average of the damage functions associated with the different building types in the land use code of the facility location where the weights are given by the frequencies of different building types in that area. Given the probabilities of the occurrence of different events, the wind intensities of these events, and the damage functions just introduced, we can compute the EAL at the facility level as in Statistics Committee of the ESCB (2023) (right panel of Figure 1).

To compute the EAL from floods at a facility level, we follow the same steps as for storms, albeit more straightforwardly. First, the event intensities associated with return periods and thus probabilities of occurrence are readily available as flood hazard maps. We access those through Delft University (Paprotny et al., 2017, 2019). Second, the damage functions for floods are calibrated at the country and land-use levels and are provided for different levels of flood depths (Huizinga et al., 2017). Third, using the facility's location, which is associated with a specific land use (see left middle and upper panels of Figure 1), we combine flood depth maps by return period with the respective damage functions to calculate the EAL for floods at a facility level.

Now that we have the expected annual loss at the facility level, we turn to our primary measure of exposure to physical risk: the EAL at the company level. To derive this measure, we aggregate the facility-level EAL values at the company level by assigning equal weights to all

[10] Unfortunately, this is the best achievable at a cross-country level in Europe. While the damage function for specific building types is available from Feuerstein et al. (2011), we do not have information on the building type of each facility. In the third step, and replicating Statistics Committee of the ESCB (2023), we use the distribution of building types for specific land usage categories by country and land usage in Europe. From the facility's location, we identify the type of land usage and calculate the damage function for the facility as the weighted average of the damage functions for different building types within that land usage category in the facility's country. For example, as shown in the top-middle panel of Figure 1, if a facility is located in a nonresidential urban area in Spain, where this land usage type comprises 69% concrete buildings and 31% weak brick buildings, the damage function for a wind intensity of 34 meter per second (m/s) is calculated as 69% times the loss ratio for concrete buildings at that wind intensity plus 31% times the loss ratio for weak brick buildings at the same wind intensity. The distribution of building types by country and land usage type is provided in Jaiswal et al. (2010).

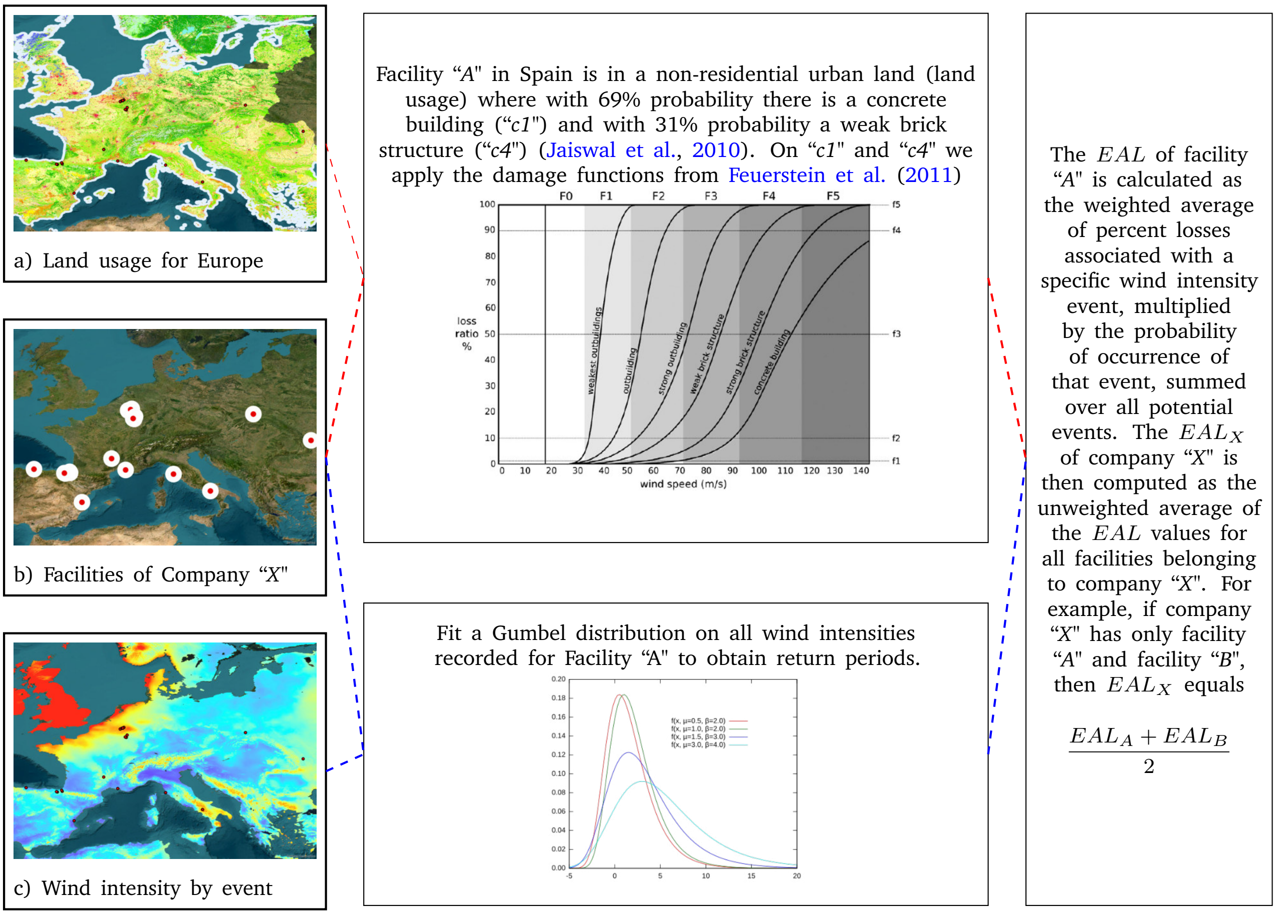


Figure 1. The relevant steps to compute the expected annual loss (EAL) from storms at a company level using the ESCB method: From left to right, we outline the steps to compute the EAL for company "X" based on the framework developed by the Eurosystem of Central Banks (ESCB) (Statistics Committee of the ESCB, 2023). Red dashed lines indicate the data sources used to compute damage functions for a specific event occurrence. Blue dashed lines represent the sources required to compute the probability of an event with a specific wind intensity, modeled using a Gumbel distribution, where the probability mass is concentrated on less extreme events. Finally, this information is combined to calculate the EAL at the facility level that is then aggregated to derive the company-level EAL.

facilities, thus not explicitly differentiating by facility importance as also implemented in Kruttli et al. (2025). Thus, for both storms and floods, the EAL at the company level is the equally weighted average of the facility-level EAL across all facilities associated with the company.

After explaining the reasoning behind calculating the EAL at the facility and company level, we now outline the exact computation process for storms as an example for both hazards. The starting point is defined by the probabilities of a storm in a particular intensity range such as wind speeds between 30 m/s and 34 m/s.[11] For each intensity range we collect the corresponding

[11] The average historical maximum three-second wind gust at 10m height in the sample is 34 m/s, with wind speeds above 30 m/s already capable of causing structural damage to most European buildings (Feuerstein et al., 2011).

damage ratio or the percentage of total value that would get destroyed in case of an event's occurrence (Feuerstein et al., 2011). Finally, we compute the EAL as the weighted average of the damage ratios across all intensity ranges, weighted by the respective probabilities of occurrence for each intensity range.

To derive the probability of an event's occurrence we need to start with the probability of an event's likelihood that a stochastic process exceeds a critical value across various return periods (e.g., 10 years). The probability of exceedance, P_{T_n}, for an event with a return period of n years, ranging from T_1 to T_n, is given by:

$$P_{T_n} = 1 - \prod_{s=T_1}^{T_n} (1 - p_s), \tag{2}$$

where p_s is the probability of occurrence of a single event. P_{T_n} can for instance be the probability that wind intensity exceeds 30 m/s in the next 10 years, $P_{T_{10}}$. We can rearrange this formula to get an expression for the probability of occurrence p_n of an event with a return period T_n:

$$p_n = \frac{P_{T_n} - 1}{\prod_{s=T_1}^{T_{n-1}} (1 - p_s)} + 1. \tag{3}$$

Logically, P_{T_n} represents the probability that a threshold is exceeded, while p_n is the probability of an event of this magnitude occurring. The probability of exceedance, P_{T_n}, is higher than p_n because it includes all more extreme scenarios, except when it corresponds to the highest return period n.

To demonstrate how to compute the probability of occurrence for different return periods, we provide the following example. Consider the return periods T_{100}, T_{50}, T_{10}. First, the probability of occurrence p_n of the longest return period T_{100}, is set equal to the exceedance probability P_{T_n} (Antofie et al., 2020). Second, from this assumption, we calculate the individual probabilities associated with the events having shorter return periods:

$$\begin{gathered} P_{T_{100}} = p_{100} = \frac{1}{100} = 0.01 \\ p_{50} = \frac{P_{T_{50}} - 1}{(1 - p_{100})} + 1 = \frac{0.02 - 1}{1 - 0.01} + 1 = 0.0101 \\ p_{10} = \frac{P_{T_{10}} - 1}{(1 - p_{100})(1 - p_{50})} + 1 = \frac{0.1 - 1}{(1 - 0.01)(1 - 0.0101)} + 1 = 0.0816 \end{gathered} \tag{4}$$

Following Antofie et al. (2020), we calculate the damage ratio for a given event as the product of the probability of occurrence, the exposed facility value, and the vulnerability factor. We use the exposed facility value as a proxy for the damage ratio associated with different event magnitudes. Specifically, the exposed value represents the proportion of a facility's value relative to the total value of the company's facilities. For example, if a company owns two facilities, each one's exposure value is 50%, meaning the damage ratio will be calculated as a fraction of 50% of the total potential damage. We assume a vulnerability factor of one, indicating that the full value of the company could be lost as a result of extreme weather events. The events are assumed to be independent, as causal relationships between them cannot currently be established Antofie et al. (2020). Therefore, the EAL at the company level is obtained by summing the product of the expected loss and the probability of occurrence for each return period by facility, and then averaging over all facilities, as explained in the right panel of Figure 1. Consequently, assuming independence of events, we express the EAL for a company i for all events expected in the next k years as:

$$EAL_{i,k} = \frac{1}{Z} \sum_{z=1}^{Z} \sum_{s=T_1}^{T_n} (p_{s,k,z} L_{s,z}), \tag{5}$$

where $p_{s,k,z}$ is the probability of occurrence of an event with return period T_s in k years for facility z.[12] Z is the total number of facilities linked to a company. Further, $L_{s,z}$ is the damage ratio associated with a single event for a given hazard, which occurs with a specific intensity for a specific facility, accounting for land use and the distribution of buildings in that area. We then average the EAL at a facility level over the Z number of facilities that belong to a company. Using the example from the previous paragraph, consider a company with two facilities in which each represents 50% of the total assets. If the damage ratio at the location of one facility, based on the damage function for a specific hazard and return period, is estimated at 20%, then the expected loss for that facility is calculated as $L_{s,z} = 0.2 \cdot 0.5$.[13]

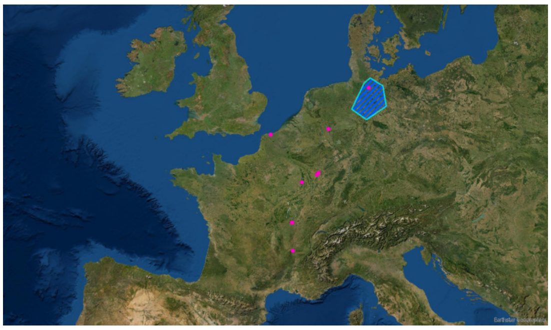
[12] For simplicity, we calculate the EAL for the next year only, setting $k = 1$, instead of using longer time periods.

[13] Here, we follow the approach suggested in Kruttli et al. (2025) who show that facility weighting does not lead to significantly different results. Weighting can be done by building size, the amount of waste produced or the amount of energy used, but data on these variables are scarce.

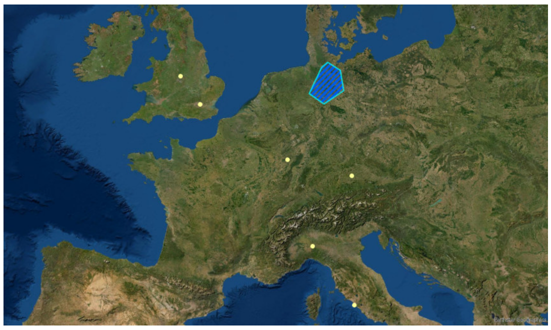
III.d The event study

The fourth step is the event study. We follow the literature on how to implement an event study to analyze the effect of extreme weather events on securities' prices (MacKinlay, 1997; Barrot and Sauvagnat, 2016). The events of interest are major storms and floods that occurred in Europe between 1 January 2014 and 31 December 2021. We define the event window for analyzing securities' prices as the five days preceding landfall for storms and two days before the occurrence for floods.[14] The event window ends 22 trading days after the event's start to allow all market participants sufficient time to adjust their positions (Lanfear et al., 2019).

Facilities are assigned to an extreme weather event if they are located in the area affected by the event. Based on this criterion, we identify publicly listed companies that owned facilities in the affected area at the time of the event. Figure 6 provides an example of our flood selection criteria, with similar criteria applying to storms. Company Y, shown in Figure 2a, has an industrial site located in the area affected by the flood in July 2017 and is therefore included in our study. In contrast, company X, in Figure 2b, 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 2. Examples of companies that are and are not affected by a flood: The blue-shaded area represents the region affected by a major flood in northern Germany on 25 July 2017. In sub-figure 2a, the pink dots indicate the locations of company Y's production facilities, one of which is in the affected area. Therefore, this company is included in our sample of affected companies. In sub-figure 2b, the yellow dots represent the locations of company X's production facilities. Since none of company X's facilities are in the affected area, this company is not included in our sample for that period.

We compute the expected and abnormal returns using the market model and the factor models developed by Fama, French, and Carhart (Fama and French, 1993; Carhart, 1997; Fama and French, 2015). Many studies have shown that various factors play a crucial role in explaining

[14] These choices are consistent with other studies, such as Lanfear et al. (2019); Nagar and Schoenfeld (2022) and the literature on early warning systems Merz et al. (2020).

the returns on equity portfolios. In this study, we use factors specifically calibrated for European developed markets, sourced from the Kenneth French Data Library. We believe this is also a conservative approach for US stocks, as cross-listed stocks are less prone to shocks Kacperczyk et al. (2021).

The occurrence of multiple events in close succession could bias our estimates, especially if the same company is affected through its facilities in the same or different affected regions. The latter could mean that investors are still updating their investment beliefs based on a previous event. We mitigate this potential bias in two ways. First, we set the estimation window for calculating the expected (normal) return to end before each event occurs. Second, we retain only those securities issued by companies affected by extreme weather events whose estimation windows do not overlap with other events of the same type. This approach helps to isolate the idiosyncratic effect of individual occurrences.

In the literature a typical estimation window to compute normal expected returns ranges from 120 to 30 days (Kruttli et al., 2025; Blanco et al., 2024). To include as many companies as possible for each event we choose a 90-day estimation window. In Figure (3), we summarize the relevant information on the length of the two windows that are relevant for the event study: the estimation period for calculating the normal expected returns and the event window during which the event takes place.

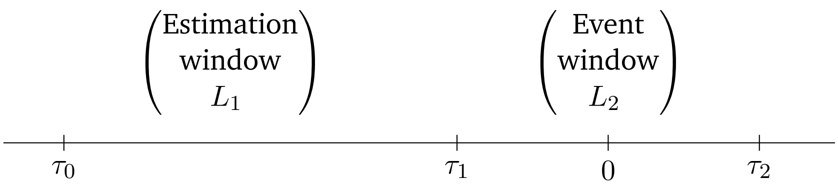


Figure 3. The relevant windows of the event study: Estimation periods L_1 and L_2 are defined in days. The estimation window for calculating normal expected returns is fixed and set at $L_1 = \tau_1 - \tau_0 = 90$ days. L_2 varies depending on the type of hazard. The event window typically starts $0 - \tau_1 = 5$ days before the event and we observe price changes until $\tau_2 - 0 = 22$ days after the event.

For the event study, we compute daily abnormal returns for each company (AR), cumulative abnormal returns for each company (CAR), and cumulative average abnormal returns across companies and events ($CAAR$). Daily abnormal returns $AR_{i,m,t}$ per company i and event m are calculated as the difference between the actual $R_{i,m,t}$ and the expected returns $ER_{i,t}$ using various expected return models for the latter. Next, we calculate CAR for each company and event by aggregating daily returns over the event window from τ_1 to τ_2. Finally, we compute the

CAARs for extreme weather events averaged across companies and events. The three necessary formulas read as follows:

$$AR_{i,m,t} = R_{i,m,t} - ER_{i,t}, \tag{6}$$

$$CAR_{i,m} = \sum_{t=\tau_1}^{\tau_2} AR_{i,m,t}, \tag{7}$$

$$CAAR = \frac{1}{N}\frac{1}{M}\sum_{i=1}^{N}\sum_{j=1}^{M} CAR_{i,m}. \tag{8}$$

In Equation (8), N represents the number of companies and M the number of events. To ensure the robustness of our results, we compute the standardized cross-sectional variance following Boehmer et al. (1991) that is robust to any variance induced by the event (Boehmer et al., 1991; Kolari and Pynnönen, 2010). Further technical details on the implementation of Boehmer et al. (1991) are provided in Appendix D.

IV Data sources and sample

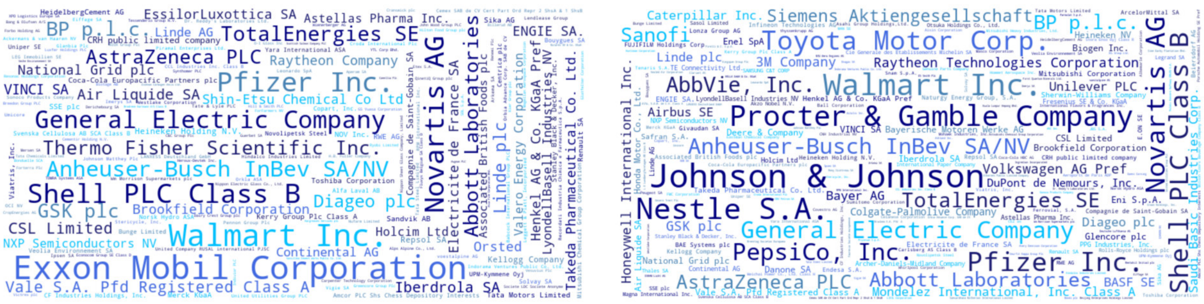
We merge several data sources to analyze how security prices react to the effect of extreme weather events. First, we obtain the locations of facilities and their links to parent companies and securities by merging the E-PRTR with Amadeus ownership data from Bureau van Dijk.[15] Second, we use facility locations, the timing and the geographical extent of extreme weather events to identify when and where companies are affected by their facilities. Third, we match the resulting dataset with daily historical returns and institutional shareholder ownership data for the parent company obtained from Factset. Additional details on the data and matching methods are provided in Appendices E and F.

We identify 4,162 European facilities linked to 1,452 publicly listed companies, only a subsample is affected. Of the companies, 168 reflect 373 facilities of which 195 were hit by storms and 178 by storms and floods. Another 516 companies reflected 1,774 facilities of which 1,596 were only affected by floods and 178 by storms and floods. The amount of facilities and companies are in line with similar studies on physical risks using facility data outside the US

[15] We assume that the ownership structure of a company does not change over four years. Therefore, we take two snapshots of Amadeus ownership (2018-2022) and extrapolate backward, assuming ownership remained unchanged for the four years prior.

(Bressan et al., 2024). We implement several measures to enhance the scientific rigor of our analysis. First, when extreme weather events occur multiple times, we only consider those with a sufficient event-free period to estimate the expected returns. This consideration ensures that the event is more likely to prompt investors to update their risk preferences, rather than being influenced by a previous event. Second, we only use securities with prices above 5 euros during the estimation period to avoid the influence of penny stocks.[16] Third, we exclude securities from the financial sector, except for the insurance sector, and include only those with at least a 10% free float. These measures account for the liquidity and microstructure effects on stocks (Barrot and Sauvagnat, 2016; Barnett et al., 2021).

Most securities included in the event study come from large-cap or mid-cap companies. Figure 4 shows the names of companies affected by floods and storms between 2014 and 2022. From the figures, we observe that some major publicly listed US companies are linked through subsidiaries and branches to facilities in Europe.[17] The sample is materially relevant in terms of economic exposure to physical risk. The companies in the analysis belong to sectors such as agriculture, manufacturing, mining, pharmaceuticals, utilities, and water. These sectors are highly exposed to weather-related disasters, as demonstrated by Dunz et al. (2021). We provide more detailed information on the sample breakdown by industry in Appendix H.a.



(a) STORMS (b) FLOODS

Figure 4. Companies affected by extreme weather events from 2014 to 2021: In sub-figure (4a), we show the names of all companies affected via their subsidiaries by storms in Europe. In sub-figure (4b), we show the companies affected via their subsidiaries by floods in Europe in the same time frame. The font size is linked to the market capitalization of the company.

The number of yearly extreme weather events increased from 2014 to 2022, with floods affecting a larger number of facilities and resulting in a higher EAL compared to storms. In Table II, we present the actual number of companies (securities) and facilities affected by extreme

[16] Stock prices in foreign currencies are converted to euro prices by Factset, so that all returns are in euros.
[17] We treat US companies with facilities in the EU as local companies for US institutional investors. In one of the robustness checks we exclude US companies from the sample and show that the results are resilient over all specifications.

weather events broken down by country and type of event. EAL is expressed as the percentage average loss over all facilities by risk type that is based on the theoretical damage functions as introduced in Section III.c. The first four columns show the key figures for storms: the absolute number of affected securities and facilities, the percentage of affected facilities as a share of the total for that country, and their average EAL across all facilities. The last four columns show the similar information for flood-affected facilities.

Table II shows that more facilities are affected by floods than by storms in Europe. Additionally, Great Britain (GB) is the country most affected by extreme weather events. On average, the EAL is considerably lower for storms compared to floods. For example, Belgium, Denmark, and Germany have EAL percentages of 0.002, 0.013, 0.003, respectively, indicating that the EAL for storms is relatively low in Europe. By contrast, floods lead to a higher EAL for Austria, Hungary, and Ireland with percentages of 12.0, 10.6, and 13.5 respectively.

The share of LIO varies widely across Europe. In Figure 5, we observe that some countries have very high levels of LIO, while others have much lower levels. For instance, Sweden has an LIO of 90%, while Luxembourg has less than 10%.

In Appendix (F.d), we provide a detailed breakdown of facilities, securities, and IO by country and sample("ALL","STORM","FLOODS"). The distribution of ownership does not vary considerably across samples.

V Investors' reactions to extreme weather events: case studies

Before analyzing the full sample, we first present the results for two case studies to illustrate the effectiveness of our method. These case studies were selected for their significant effects on Europe in terms of damages. In the first case study, we examine Storm Ciara in early February 2020, which was highlighted in EIOPA (2022). While the worst effects were felt in Ireland and GB, Ciara caused widespread wind and flood damage across Europe. The second case study involves the July 2021 floods which severely affected Belgium, Germany, and the Netherlands and rank among the most damaging floods in European history as the estimated damages were €10 billion (EIOPA, 2022).

The key findings for the two events are shown in Table (III), with the strongest negative abnormal return observed for Storm Ciara. The table presents the CAAR across different models of the expected returns and was calculated over three distinct periods. The first period covers five

	STORM				FLOOD				TOTAL	
	Sec.	Facility	% Fac.	EAL_i	Sec.	Facility	% Fac.	EAL_i	Sec.	Facility
AT	-	-	-	0.0008	10	30	0.72	12.01	36	88
BE	12	21	0.5	0.0024	13	17	0.41	9.82	105	187
CH	-	-	-	0.0011	12	19	0.46	13.32	35	55
CY	-	-	-	0.0017	-	-	-	-	1	2
CZ	-	-	-	0.0013	15	36	0.86	9.36	66	104
DE	7	11	0.26	0.0025	89	196	4.71	9.98	228	564
DK	7	10	0.24	0.0128	1	3	0.07	8.97	24	38
EE	-	-	-	0.0020	-	-	-	7.51	11	24
ES	-	-	-	0.0009	33	111	2.67	10.10	105	287
FI	-	-	-	0.0016	-	-	-	8.07	46	121
FR	15	25	0.6	0.0014	111	480	11.53	8.30	185	746
GB	93	261	6.27	0.0016	132	580	13.94	8.21	156	885
GR	-	-	-	0.0009	1	1	0.02	8.81	7	14
HR	-	-	-	0.0032	1	2	0.05	9.61	11	12
HU	-	-	-	0.0025	-	-	-	10.62	18	32
IE	19	25	0.6	0.0020	16	23	0.55	13.51	33	42
IS	-	-	-	-	-	-	-	-	2	3
IT	-	-	-	0.0005	47	204	4.9	10.46	121	385
LI	-	-	-	0.0041	-	1	0.02	-	1	1
LT	-	2	0.05	0.0015	-	-	-	8.83	5	6
LU	1	1	0.02	0.0012	1	1	0.02	4.20	2	2
NL	11	14	0.34	0.0018	19	34	0.82	9.74	28	40
PL	-	-	-	0.0022	9	21	0.50	9.38	125	312
PT	-	-	-	0.0012	-	-	-	8.03	28	40
RO	-	-	-	0.0008	6	15	0.36	11.97	13	45
RS	-	-	-	0.0006	-	-	-	9.17	3	6
SE	3	3	0.07	0.0021	-	-	-	10.98	51	113
SI	-	-	-	0.0003	-	-	-	8.81	6	8
Total	168	373	8.96	0.0020	516	1774	42.62	9.59	1,452	4,162

Table II. Affected companies and facilities by country: In this table, we show the number of unique affected publicly listed companies owning these facilities (Sec.=Security), the actual number of unique affected facilities (Facility), and the percentage of affected facilities as a percentage of total facilities in a country (%Frac). However, facilities might be affected several times over the years by extreme weather events, which would lead to a higher number of affected facilities. Additionally, the theoretical EAL is the expected annual loss per country averaged over the affected facilities, based on the model in Section III.c. The final column represents all companies and facilities, affected and not affected, in a country. The average is computed from 2014 to 2021, and data on facilities are obtained from the E-PRTR.

days prior to one day before the event for storms, and two days prior to one day before the event for floods. The second period spans from the event date to 10 days after, and the third period extends from 11 days to 22 days post-event. In columns 1 through 4, we display the CAAR for each expected return model for Storm Ciara, while columns 5 through 8 show the corresponding results for the floods. We observe that the negative surprise from Storm Ciara ranged from -2.72 to -2.91 percentage points (p.p.) over the 10 days following the event. A similar negative surprise occurs for the floods, but it only materializes from 11 to 22 days after the event, reaching a

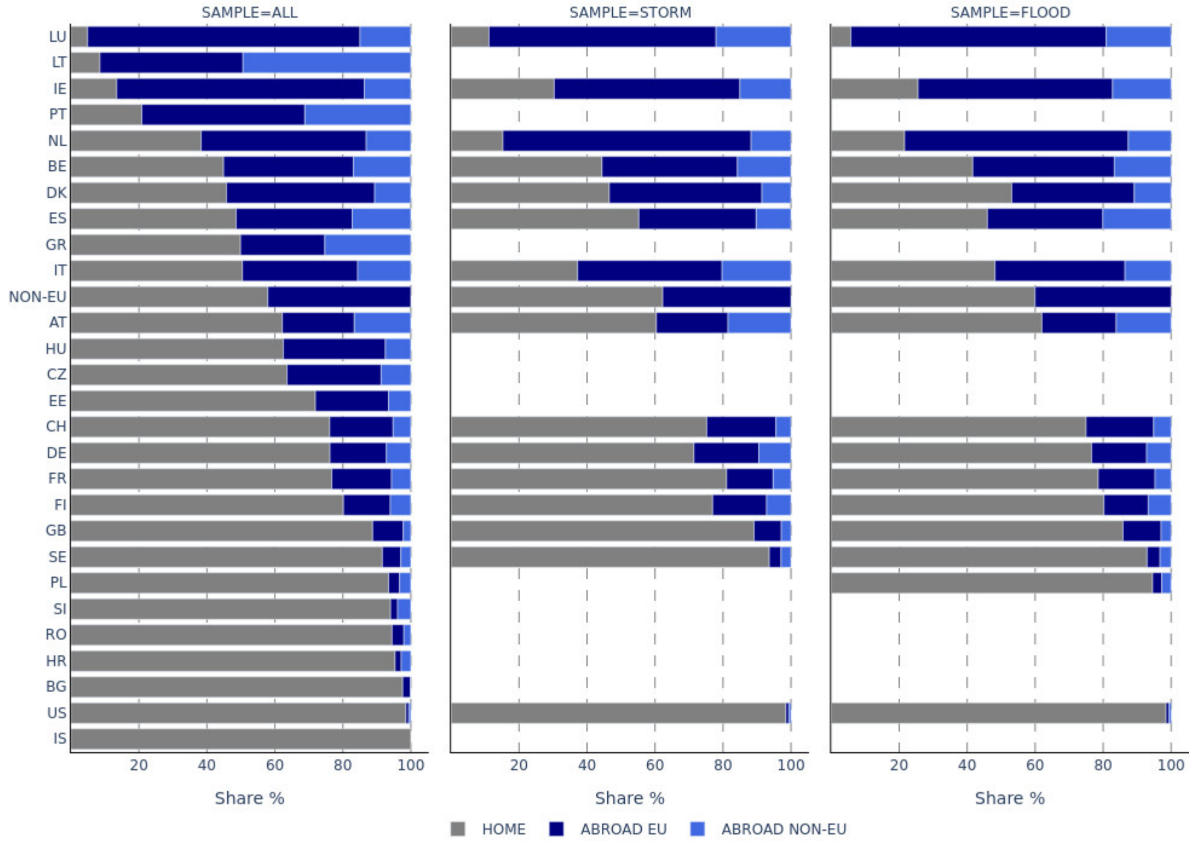


Figure 5. Institutional ownership ownership of securities by country: This figure presents equity ownership segmented by the issuing country and type of extreme weather event. For simplicity, three groups are highlighted to show geographic ownership patterns. If an institutional owner (IO) is based in the same country as the company it owns, this ownership is classified as "HOME." If the IO is based in a different country within the EU, it is categorized as "ABROAD-EU." Finally, if the IO is located outside the EU, it is classified as "ABROAD NON-EU." The right panel shows the distribution of ownership for all companies matched with publicly listed equities, while the two right-hand panels display the ownership percentages for the sample of companies affected by storms and floods.

negative CAAR of -0.61 to -2.16 p.p. This return indicates that for floods, investors require more time to fully price in the negative effect of such significant events.

To support the case study, we show whether the affected companies disclose information on their exposure to or effect from extreme weather events in their annual reports. Table (IV) provides excerpts from the 2020 and 2021 annual reports of some of the companies affected by Storm Ciara or the summer floods. These excerpts disclosed that these companies acknowledged their exposure to extreme weather events. Using these case studies, we validate our implementation of the method developed by the Statistics Committee of the ESCB (Statistics Committee of the ESCB, 2023).

	CAAR							
	Storm Ciara February 2021				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 Storm Ciara in 2020 and floods in 2021: In Table (III), we show the $CAAR$ for Storm Ciara in 2020 and the floods in 2021. The first period covers five days to one day before storms and two days to one day before floods. The second spans the event date to 10 days after, and the third from 11 to 22 days post-event. We use the following models to estimate the normal expected returns: Mkt, $3F$, $4F$, and $5F$. N is the number of uniquely affected companies. The numbers in brackets below the average estimates are standard deviations computed using the test statistics from Boehmer et al. (1991).

	Company (year of annual report)	Annual Report Excerpt
Ciara 2020	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 (2021)	*"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 (2021)	*"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 (2021)	*"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. Extracts from annual reports related to risks from extreme weather events for companies with negative CAAR during Storm Ciara in 2020 and the floods of July 2021: Extracts from 2020 or 2021 annual reports. These reports highlight the risk exposures of companies affected by Storm Ciara in early 2021, as well as the risk exposures of companies affected by the summer floods of 2021 in Belgium, the Netherlands, and Germany.

VI Results for the full sample

Building on the insights obtained from the case studies, we now extend our analysis to the entire sample of companies affected by extreme weather events. In this section, we test the four hypotheses introduced in Section (II).

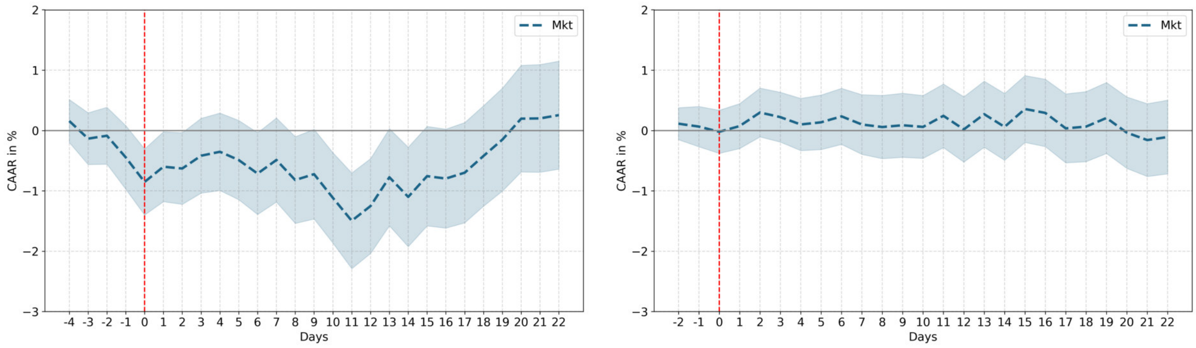
VI.a Type of extreme weather event

The first hypothesis states that *"Securities of firms affected by storms experience more negative cumulative average abnormal returns (CAAR) compared to those affected by floods."* To test this hypothesis, we examine whether the CAARs are significantly different from zero within a classical event study framework. The evidence from the entire sample supporting this hypothesis is presented in Table V. The table presents the CAAR across various estimation windows and models of the expected returns, calculated over four distinct periods. The first three periods resemble those in Table (III). The additional period covers five days before to 22 days after the event for storms, and two days before to 22 days after the event for floods. We observe a discrepancy between investors' reactions to storms and floods. Investors' negative reactions to storms are consistent across all estimation models, with CAAR always negative and ranging from -0.72 to -0.99 percentage points (p.p.) in the period between the event date and 10 days after. For floods, however, CAAR shows a slightly positive trend before the event, albeit by only a few basis points and a negative reaction within 10 days post-event appears only in the $4F$ and $5F$ models; there is a lack of consistency across all models.

	CAAR							
	STORMS				FLOOD			
	Mkt	$3F$	$4F$	$5F$	Mkt	$3F$	$4F$	$5F$
(-5/-2:-1)	-0.22***	-0.40***	-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 for storms versus floods: This table gives a summary of the $CAAR$ for storms and floods for the whole sample for all estimation models of the expected returns (Mkt, $3F$,$4F$,$5F$). The first period covers five to one day before storms and two to one day before floods. The second spans the event date to 10 days after, and the third from 11 to 22 days post-event. The last period covers five days before to 22 days after the event for storms, and two days before to 22 days after the event for floods. The numbers in brackets below the average estimates are standard deviations using the t-statistic from (Boehmer et al., 1991). N is the number of companies. Note that facilities, and therefore companies, can be affected multiple times over the years. Consequently, these numbers will differ from those in Table II. Additionally, companies can have facilities affected by an extreme weather event in multiple countries.

We provide additional evidence supporting H1 by plotting CAAR and its confidence intervals across the entire event window. In Figure (6), the horizontal axis shows days relative to the event and the vertical axis shows CAAR in percentage points. The estimates in the graph are based on the market model, with confidence intervals calculated using the event-induced variance measure from Boehmer et al. (1991). The results consistently demonstrate a negative cumulative risk-adjusted investor reaction to storms that reaches an average of -0.8 percentage points (p.p.) on the event date and up to -1.5 p.p. 11 days post-event. For floods, no significant deviation from zero is evident. Furthermore, Appendix (G.a) shows these results persist over time and are not driven by specific outliers, such as the Covid-19 pandemic.



(a) STORM (b) FLOOD

Figure 6. CAAR for all weather-related disaster types: Sub-figure 6a depicts the CAAR for companies affected by storms, while sub-figure 6b shows the CAAR for companies with facilities affected by floods. The horizontal axis represents the days relative to the event date, and the vertical axis displays the $CAAR$ in percentage terms. For storms, forecasts predict an event's occurrence in a specific region up to five days in advance that allows investors to anticipate the storm's effect, resulting in a negative CAAR even before the event occurs. In contrast, flood forecasts are typically available only two days in advance, providing investors with less time to anticipate and react to the event.

VI.b Market segmentation

In the previous section, we demonstrated that the type of extreme weather event significantly influences its effect on stock prices. Here, we extend the analysis to examine the role of market segmentation, specifically testing whether a higher share of LIO positively affects stock prices during extreme weather events. This analysis is based on the assumption that LIO have superior knowledge of their local investments. To investigate, we test H2 through 4, as outlined in Section II. First, we begin with H2: *"The greater the degree of local institutional ownership in a security before an event, the higher the cumulative abnormal returns (CAR) around the event's occurrence."* This hypothesis leans in the direction of the LIO having superior information on local stocks. We follow three approaches: a baseline model and two distinct channels through which to test the validity of the information advantage hypothesis.

We define the baseline model as follows:

$$CAR_{Model,i,t} = \beta_0 + \beta_1 LIO_{i,t-1} + \beta_2 Post_t + \beta_3 LIO_{i,t-1} \cdot Post_t + \Psi_t + \epsilon_{i,t}, \tag{9}$$

where $CAR_{Model,i,t}$ represents the CARs for company i on event day t that is estimated using the different models of the expected returns presented in Section III.d. $LIO_{i,t-1}$ is the share of local institutional ownership for security i in the quarter prior to the event. $Post_t$ is a dummy variable that equals one if the date is on or after the event day, and zero otherwise. Ψ_t represents time fixed effects which account for variation in the estimates solely due to time-related factors, and $\epsilon_{i,t}$ is the error term.

Second, we test H3: *"The positive effect of local institutional ownership is greater when the affected facilities are located in regions with higher exposure to extreme weather events."* Therefore, we introduce a triple interaction term between LIO and the days following the event. Additionally, we include all relevant double interaction terms to account for potential sources of heterogeneity in this analysis, as recommended by (Olden and Møen, 2022). Consequently, the model to test H3 is as follows:

$$\begin{aligned}CAR_{Model,i,t} =& \beta_0 + \beta_1 LIO_{i,t-1} + \beta_2 EAL_i + \beta_3 Post_t + \beta_4 LIO_{i,t-1} \cdot Post_t + \\ & \beta_5 LIO_{i,t-1} \cdot EAL_i + \beta_6 EAL_i \cdot Post_t + \beta_7 LIO_{i,t-1} \cdot Post_t \cdot EAL_i + \\ & \Psi_t + \epsilon_{it}\end{aligned} \tag{10}$$

In Equation (10), EAL_i is a company's exposure to the extreme weather event type as a percentage of total tangible assets. We compute EAL at the facility level and average it with equal weights over all facilities that are linked to a company. EAL_i is fixed over the whole period for every company as this is based on future events' probabilities as explained in Section III.c. We test the hypothesis regressing Equation (9), with time fixed effects and clustering for time as suggested in Petersen (2009), where time is the event date.

Third, we test whether a longer distance between the affected facility and its headquarters reduces the positive effect of LIO. This model builds on the concept of Pellegrino et al. (2024), where investment barriers increase with distance. We calculate the distance between a facility and its headquarters using latitude and longitude data, following the approach of Coval and Moskowitz (2001). This approach allows us to test H4: *" The positive effect of LIO weakens as the distance between a facility and the company's headquarters increases"*. We use the following model to test this hypothesis:

$$\begin{aligned}CAR_{Model,i,t} =& \beta_0 + \beta_1 LIO_{i,t-1} + \beta_2 ln(Dist_i) + \beta_3 Post_t + \beta_4 LIO_{i,t-1} \cdot Post_t + \\ & \beta_5 LIO_{i,t-1} \cdot ln(Dist_i) + \beta_6 ln(Dist_i) \cdot Post_t + \beta_7 LIO_{i,t-1} \cdot Post_t \cdot ln(Dist_i) + \\ & \Psi_t + \epsilon_{it},\end{aligned} \tag{11}$$

where $ln(Dist_i)$ is the natural logarithm of the distance in kilometers between the affected facility and the headquarters of the company.

Before we go to the results, we first provide the descriptive statistics of the variables used in the models from Equations (9), (10) and (11) in Table (VI). The CAR variables and the distance variable $Dist$ are winsorized. The daily average CAR, denoted as μ, is negative across all models for both storm and flood events. For floods, the CAR has a lower standard deviation than for storms, while the minimum and maximum values are quite similar in both samples. The median LIO for storms exceeds that for floods by almost 10 percentage points, although the volatility is very similar. However, the LIO distribution for floods shows a higher density closer to the median compared to storms. The EAL is higher for floods than for storms. Similarly, companies affected by both storms and floods have similar volatilities in $Dist$.

		$CAR_{Mkt,i,t}$	$CAR_{3F,i,t}$	$CAR_{4F,i,t}$	$CAR_{5F,i,t}$	$LIO_{i,t-1}$	EAL_i	$ln(Dist_i)$
STORM	μ	-0.77	-1.12	-0.88	-1.12	42.31	0.0022	1.89
	σ	5.63	5.59	5.74	5.67	30.77	0.0022	0.31
	min	-18.68	-18.97	-17.94	-17.83	0.47	0.0000	-1.08
	$P_{25\%}$	-3.54	-3.81	-3.75	-3.98	18.43	0.0010	1.77
	$P_{50\%}$	-0.82	-0.91	-0.80	-0.96	33.00	0.0016	1.90
	$P_{75\%}$	1.98	1.62	1.78	1.71	73.42	0.0029	2.15
	max	13.62	12.55	13.87	12.75	95.96	0.0110	2.22
	N	5,677	5,677	5,677	5,677	5,677	5,677	5,565
FLOOD	μ	-0.15	-0.08	-0.32	-0.15	34.37	9.57	1.74
	σ	5.01	4.88	5.42	4.93	29.75	3.67	0.72
	min	-16.95	-15.78	-19.44	-16.06	0.04	3.66	-5.29
	$P_{25\%}$	-2.59	-2.57	-2.86	-2.69	12.69	6.89	1.73
	$P_{50\%}$	-0.07	-0.11	-0.21	-0.15	23.53	8.72	1.83
	$P_{75\%}$	2.40	2.37	2.38	2.34	51.06	12.04	1.99
	max	12.08	12.18	12.92	12.25	97.11	19.49	2.21
	N	14,022	14,022	14,022	14,022	14,022	14,022	13,776

Table VI. Descriptive statistics for the key regression variables: This table provides descriptive statistics for the main variables used in the regressions. The μ and σ represent the daily mean and standard deviation in the sample, respectively, expressed as percentages. The $P_{25\%}, P_{50\%}, P_{75\%}$ are the percentiles of the distribution. The distance is defined as the natural logarithm of the kilometers between a facility and its company's headquarters. The previous quarter's LIO and EAL are expressed as percentages. We compute EAL at the facility level and average it by using equal weights across all facilities linked to a company by the name-matching algorithm. All variables are winsorized at the 1^{st} and 99^{th} percentiles to mitigate the effect of outliers. N represents the number of CAR observations by company and date on which the descriptive statistics are based.

We now turn to the main results of the regressions, presented in Table (VII). The results for Equation (9) are shown in column (1) for both storms and floods, supporting H1. The findings indicate that a higher LIO prior to the event positively effects CAR on the event date, especially for events with greater uncertainty, in this case as storms. The variable LIO_{t-1}, representing the share of local institutional ownership in the quarter preceding the weather event, shows a positive and significant effect on CAR. This effect remains significant when LIO is interacted with the dummy variable $Post$.

For storms, a percentage point increase in LIO leads to a 0.013 percentage point increase in CAR. After the event, the effect strengthens, with a percentage point increase in LIO_{t-1} leading to a 0.023 percentage point increase in CAR. Considering that $Post$ is associated with an average decrease in $CAR_{t,Mkt}$ of -2.66 percentage points, LIO_{t-1} mitigates this negative effect by approximately 1.3 percentage points.

The results of Equation (10) for storms and floods are presented in column 2 and provide mixed evidence for H2. The primary coefficient of interest in this regression is the triple interaction term $LIO_{t-1} \cdot Post \cdot EAL_i$. Column (2) confirms the results of the baseline model for storms, indicating that companies with a greater share of LIO before the event experience less severe negative abnormal returns when EAL_i is higher. This experience means that LIO are better informed about the type of risk, reducing the surprise effect of the event. However, in the case of floods (also shown in column (2)), local ownership does not appear to mitigate the negative effect of the event. This contrast means that local knowledge plays a more substantial role in reducing adverse outcomes when the event carries greater uncertainty about when it will occur and what its effect will be.

	$CAR_{t,Mkt}$					
	STORM			FLOOD		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
β_0	0.0064	-0.0008	1.0003**	0.2610	0.3110	0.3816
	(0.2538)	(0.2565)	(0.4665)	(0.2362)	(0.2250)	(0.4135)
LIO_{t-1}	0.0131***	0.0060	0.0142	0.0026	0.0014	0.0049
	(0.0021)	(0.0039)	(0.0111)	(0.0027)	(0.0031)	(0.0073)
$Post_t$	-2.6585***	-2.0402***	-3.6713***	-0.6898**	-0.7927***	-1.0638*
	(0.3216)	(0.3501)	(0.6330)	(0.2850)	(0.2870)	(0.5619)
$LIO_{t-1} \cdot Post_t$	0.0226***	0.0139***	0.0946***	0.0035	0.0062	0.0053
	(0.0030)	(0.0050)	(0.0144)	(0.0038)	(0.0044)	(0.0099)
EAL_i		-52.949**			-0.0220	
		(25.107)			(0.0288)	
$LIO_{t-1} \cdot EAL_i$		3.1644**			0.0007	
		(1.2943)			(0.0005)	
$Post_t \cdot EAL_i$		-165.65***			0.0473	
		(35.864)			(0.0341)	
$LIO_{t-1} \cdot Post_t \cdot EAL_i$		3.6874**			-0.0018**	
		(1.4834)			(0.0007)	
$ln(Dist_i)$			-0.1779***			-0.0230
			(0.0605)			(0.0517)
$LIO_{t-1} \cdot ln(Dist_i)$			0.0002			-0.0003
			(0.0015)			(0.0011)
$Post_t \cdot ln(Dist_i)$			0.1453*			0.0647
			(0.0866)			(0.0735)
$LIO_{t-1} \cdot Post_t \cdot ln(Dist_i)$			-0.0094***			-0.0004
			(0.0019)			(0.0014)
N	5,593	5,593	5,593	14,022	14,022	14,022
R^2	0.0322	0.0514	0.0541	0.0014	0.0020	0.0016
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Table VII. Effect of local institutional ownership, expected annual loss, and distance on cumulative abnormal returns: This table shows the fixed effects regression where $CAR_{it,Mkt}$ is the dependent variable. The explanatory variables are: $LIO_{(i,t-1)}$ or the quarterly lagged percentage of local institutional ownership calculated using the measure by Coeurdacier and Rey (2013) and definitions from Coval and Moskowitz (2001), EAL_i, or the expected annual loss. $Post_t$ which is a dummy equal to one for the days at or after the event and $ln(Dist_i)$ that is the logarithm of the distance in kilometers between the facility and the headquarters as suggested in (Pellegrino et al., 2024). Covariance is clustered by time (Petersen, 2009). N is the number of $CAR_{t,Mkt}$ by day and company over which regressions are computed.

Finally, column (3) shows the results from testing regression (11) that provide support for H4. In this specification, we are particularly interested in the triple interaction $LIO_{(t-1)} \cdot Post \cdot ln(Dist_i)$ as it shows that the positive effect of the information advantage decreases with the distance from the headquarters, which is by definition closer to LIOs. The results of this specification are presented in column (3) for storms (STORM) and floods (FLOOD) in Table (VII). Column (3) confirms the results of the baseline model for STORM. Additionally, column (3) shows that the interaction term is negative and decreases the information precision with increasing distance. For example, for a 100% increase in distance, then CAR decreases by 0.009 percentage points for every percentage point increase in $LIO_{(t-1)}$, thus supporting H4.[18]

VII Robustness checks

In this section, we discuss the robustness checks conducted to test the resilience of our results. We replicate the analysis from Section VI.b. Instead of using only the market model, we also use the 3F, 4F, and 5F models to calculate the CAR. This robustness test shows that the results are not materially affected by different models to derive the expected returns. We also add two specific robustness checks. First, we repeat the regression excluding companies from the US as they constitute a large share of our sample and could disproportionately influence the outcomes. Second, we omit the year 2020 to account for the potential effect of the Covid-19 pandemic on our results.

Adding additional risk factors to the CAR estimation models does not lead to changes in the results of the main model for testing H2. The results remain consistent when repeating regression (9) using the 3F, 4F and 5F models to estimate the expected returns and CAR. The findings of these different estimation models are presented in column (1) of Tables (XI, XII, and XIII) in Appendix (I). These tables follow the same structure as Table (VII). The results for CAR_{Mkt} are also confirmed by the other estimation models. Thus, we conclude that greater LIO mitigates the negative effect of uncertainty arising from extreme weather events and that this result is resilient to different financial risk specifications. Also if we exclude US companies or remove the year 2020 from the sample, it does not alter our findings for H2. The results from these two robustness checks can be found in Appendix (J).

We also test H3 by running regressions using different factor models to estimate the expected returns and CAR. The results are presented in column (2) of Tables XI, XII, and XIII in Appendix I. The findings for H3 remain valid across all different estimation models. We find that the results are robust when excluding US companies from the analysis, but not when excluding the year 2020. Specifically, when the year 2020 is removed from the sample, the coefficient for the interaction term $LIO_{t-1} \cdot Post \cdot EAL_i$ changes sign, as illustrated in Appendix J. However, the positive effect of $LIO_{t-1} \cdot Post$ remains. This finding indicates that the EAL measure would

[18] We also test hypotheses H2 to H4 simultaneously using a single-step regression of factor loadings on raw returns, but this analysis does not yield additional insights.

benefit from additional information on insurance coverage, which is not captured by the measure but might be known to investors.

Finally, the results are also resilient to the different CAR estimation models and the robustness checks for H4. The results for the different estimation models and the robustness checks are available in column (3) of Tables (XI, XII and XIII) and in section (J). After these results we can fully support H4 that means this information channel is resilient in all cases and that greater distance from the event occurrence does influences the results.

VIII Conclusion

Our analysis explores how extreme weather events effect securities prices and whether the surprise is influenced by informational advantages. We compare storms and floods because early warning systems show that they have different types of effects and uncertainties about locations. Our empirical method 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 (LIO) reduces this negative surprise by 1.3% for every additional percentage point of local ownership. Drawing from the findings summarized above, our research substantiates the theories posited in the literature (Coval and Moskowitz, 2001; Van Nieuwerburgh and Veldkamp, 2009; Kruttli et al., 2025). This empirical validation echoes other studies and contributes to our understanding of the relationship between extreme weather events and the prices of securities (Alok et al., 2020; Huynh and Xia, 2021; Kruttli et al., 2025). These results are in line with the literature (Pellegrino et al., 2024; Kruttli et al., 2025; Blanco et al., 2024).

Our work has several limitations: we lack precise information on the extent to which individual facilities are affected and on the relative importance of these facilities to the company. However, as shown in Kruttli et al. (2025), this limitation does not appear to significantly affect the results. The facilities reported in the E-PRTR are generally key facilities for the reporting companies, as they must be reported only if they exceed certain waste thresholds, which also suggests higher production levels.

We contribute to two streams of literature. First, we examine the role of local institutional ownership in securities' performance under exogenous shocks, focusing on market segmentation and event-driven uncertainty. Second, we contribute to the literature on the effect of extreme weather events on asset prices by using granular facility-level data. Our approach leverages innovative, open-source data for financial analysis.

Our findings have important implications for policymakers and finance practitioners. For policymakers, our research underscores the value of publicly available sources, such as E-PRTR and Copernicus, in supporting climate finance analysis. However, our study also highlights the need for harmonizing data across countries to improve the accuracy and completeness of these sources. For finance professionals, the informational barriers and local equity preferences that influence market adjustments following extreme weather events emphasize the importance of considering these factors in portfolio strategies. Additionally, diminishing informational distances for non-local investors would likely alleviate price surprises before and after the events.

We acknowledge that channels other than the information channel may help explain our findings. Although non-local investors have higher demand elasticity, local investors whose demand is less price-elastic due to lower transaction costs and tax advantages seem to cushion negative price impacts (Koijen et al., 2019).[19]

In conclusion, our study provides leads for future research on climate finance. The research can be extended to other countries with E-PRTR locational data, enabling a broader evaluation of the effects of extreme weather events on financial markets. It would be particularly valuable to examine how disclosure of insurance coverage affects investors' reactions to extreme weather events. In regions with state-backed insurance programs, market dynamics, especially in flood-prone areas, may shift notably. Finally, we advocate for an interdisciplinary approach that integrates insights from finance, climatology, and economics to unravel the complex interactions among extreme weather events, investor behavior, and financial markets.

[19] Local investors may exhibit more inelastic demand due to transaction costs or differing tax treatments, as documented in the home bias literature (Coeurdacier and Rey, 2013).

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A Theoretical model

In this appendix, we show how impact uncertainty and incidence uncertainty of extreme weather events affect expected stock returns in a segmented market. The model is derived from Merton (1987) and Kruttli et al. (2025).

We consider a two-period model with K firms in the economy. Additionally, two other securities are available for trading in the market. The first is a risk-free asset offering a return of R_f, and the second is a forward contract settled in cash based on the realized market factor $\tilde{Y}$. This common market factor is a random variable with $\mathbb{E}(\tilde{Y}) = 0$ and $\mathbb{E}(\tilde{Y}^2) = 1$. The return on the forward contract is given by:

$$\tilde{R}_{K+1} = \bar{R}_{K+1} + \tilde{Y}, \tag{12}$$

where $E(\tilde{R}_{K+1}) = \bar{R}_{K+1}$.

Investor j assigns a portion of its wealth, represented by $w_{i,j}$, to firm i. Similarly, the fraction of wealth that investor j allocates to the forward contract is $w_{K+1,j}$. We define the return on investor j's portfolio as follows:

$$\tilde{R}_j = \bar{R}_j + b_j\tilde{Y} + \tilde{\epsilon}_j + \tilde{g}_j\tilde{\theta}_j. \tag{13}$$

The total exposure of investor j to the market factor is given by:

$$b_j = \sum_{i=1}^{K} w_{i,j}b_i + w_{K+1,j}, \tag{14}$$

where b_i is the exposure of a stock to the common market factor. The portfolio return has two idiosyncratic factors. The first one is related to firm specific risk and given by:

$$\tilde{\epsilon}_j = \sum_{i=1}^{K} w_{i,j}\sigma_i\tilde{\epsilon}_i. \tag{15}$$

The second one is related idiosyncratic climate-related shocks:

$$\tilde{g}_j\tilde{\theta}_j = \sum_{i=1}^{K} w_{i,j}\tilde{g}_i\tilde{\theta}_i, \tag{16}$$

where g_i is the effect of the extreme event on a stock and is a random variable with mean

$\mu_{g,i}$ and variance $\sigma^2_{g,i}$. Further, θ_i is a Bernoulli distributed random variable $\tilde{\theta}_{i,t+1} \sim B(1,\phi)$ that indicates whether the firm who issued the stocks is hit by an event, with probability ϕ.

In Eq. (13) $\bar{R}_j$ is the expected portfolio return without the idiosyncratic extreme weather risk factor as given in Merton (1987):

$$\bar{R}_j = R_f + b_j(\bar{R}_{K+1} - R_f) + \sum_{i=1}^{K} w_{i,j}\Delta_i. \tag{17}$$

To derive this return, we use the fact that the portfolio share allocated to the risk-free asset is given by $w_{K+2,j} = 1 - \sum_{i=1}^{K+1} w_{i,j}$ and set $\Delta_i \equiv \bar{R}_i - R_f - b_i(\bar{R}_{K+1} - R_f)$.

The expected return and variance of investor j's portfolio can then be expressed as:

$$E(\tilde{R}_j) = \bar{R}_j + \sum_{i=1}^{K} w_{i,j}\mu_{g,i}\phi, \tag{18}$$

and

$$\text{Var}(\tilde{R}_j) = b_j^2 + \sum_{i=1}^{K} w_{i,j}^2(\sigma_i^2 + \sigma_{g,i}^2\phi + \mu_{g,i}^2\phi(1-\phi)). \tag{19}$$

We incorporate market segmentation as in Merton (1987) by assuming that investors are limited to investing only in securities they are familiar with. For each investor j, the set of securities they are aware of is denoted by S_j, while the set of securities they are unaware of is denoted by S_j^c.

For an investor with mean-variance preferences, the maximization problem is:

$$\max_{b_j, w_j} \left[E(\tilde{R}_j) - \frac{\delta_j}{2}\text{Var}(\tilde{R}_j) - \sum_{i=1}^{K} \lambda_{i,j} w_{i,j} \right], \tag{20}$$

where w_j is a vector with elements $w_{i,j}$. The final term represents the constraint that investors are only able to invest in securities they are aware of. The Kuhn-Tucker multiplier $\lambda_{i,j}$ is zero if security i is included in investor j's knowledge set, S_j. If the investor is unaware of security i, then $w_{i,j} = 0$. The first-order conditions with respect to b_j and w_j are

$$\bar{R}_{K+1} - R_f - \delta_j b_j = 0, \tag{21}$$

and

$$\Delta_i + \mu_{g,i}\phi - \delta_j w_{i,j}(\sigma_i^2 + \sigma_{g,i}^2\phi + \mu_{g,i}^2\phi(1-\phi)) - \lambda_{i,j} = 0, \quad i = 1, \ldots, K. \tag{22}$$

The solutions for the market factor exposure and the portfolio weights for each firm are given by

$$b_j = \frac{\bar{R}_{K+1} - R_f}{\delta_j}, \tag{23}$$

and

$$w_{i,j} = \frac{\Delta_i + \mu_{g,i}\phi}{\delta_j(\sigma_i^2 + \sigma_{g,i}^2\phi + \mu_{g,i}^2\phi(1-\phi))}, \quad \text{for } i \in S_j, \tag{24}$$

$$w_{i,j} = 0, \quad \text{for } i \in S_j^c, \tag{25}$$

$$w_{K+1,j} = b_j - \sum_{i=1}^{K} w_{i,j} b_i, \tag{26}$$

$$w_{K+2,j} = 1 - b_j + \sum_{i=1}^{K} w_{i,j}(b_i - 1). \tag{27}$$

Using the solutions for individual investor demand, we can aggregate the data across the N investors in the economy to derive equilibrium asset prices and expected returns. We assume that all investors share the same level of risk aversion and initial wealth, specifically $\delta_j = \delta$ and $W_j = W$. As a result, the exposure to the market factor presented in Equation (23) is uniform for all investors:

$$b_j = b = \frac{\bar{R}_{K+1} - R_f}{\delta}. \tag{28}$$

From all N investors only N_i investors know about security i. Using equation Equation (24), we can write the aggregate demand for security i as

$$D_i = N_i W \frac{\Delta_i + \mu_{g,i}\phi}{\delta(\sigma_i^2 + \sigma_{g,i}^2\phi + \mu_{g,i}^2\phi(1-\phi))}. \tag{29}$$

The equilibrium of total wealth is $M \equiv NW$. The value of security i as a fraction of the total market capitalisation is:

$$\frac{V_i}{M} = x_i = \frac{q_i(\Delta_i + \mu_{g,i}\phi)}{\delta(\sigma_i^2 + \sigma_{g,i}^2\phi + \mu_{g,i}^2\phi(1-\phi))}, \tag{30}$$

where q_i is the share of investors who know about the stock, $q_i = N_i/N$, and $V_i = D_i$ in equilibrium. Using the definition of Δ_i together with Equations (28) and (30), the equilibrium expected return for stock i can be expressed as:

$$\mathbb{E}(\tilde{R}_i) = \bar{R}_i + \mu_{g,i}\phi = R_f + b_i b\delta + \Delta_i + \mu_{g,i}\phi, \tag{31}$$

or

$$\mathbb{E}(\tilde{R}_i) = R_f + b_i(\bar{R}_{K+1} - R_f) + \frac{\delta x_i(\sigma_i^2 + \sigma_{g,i}^2\phi + \mu_{g,i}^2\phi(1-\phi))}{q_i}, \tag{32}$$

where $\sigma_{g,i}^2\phi$ reflects the *impact uncertainty*, that is, the expected variance of the event's effect on the stock return, and $\mu_{g,i}^2\phi(1-\phi)$ captures the *incidence uncertainty*, that is, the uncertainty about whether the stock will be hit by the event.

We infer the following three observations from Equation (32):

1. An increase in impact uncertainty $\sigma_{g,i}^2\phi$ leads to higher expected returns,
2. An increase in incidence uncertainty $\mu_{g,i}^2\phi(1-\phi)$ leads to higher expected returns,
3. A lower fraction of investors familiar with the stock q_i leads to higher expected returns.

Further, the impact probability ϕ on expected returns is hump-shaped. We take the first derivative of the expected return w.r.t. probability ϕ:

$$\frac{d}{d\phi}\mathbb{E}(\tilde{R}_i) = \frac{\delta x_i}{q_i}\left(\sigma_{g,i}^2 + \mu_{g,i}^2(1-2\phi)\right). \tag{33}$$

Clearly then:

- For $\phi < \frac{1}{2}\left(1 + \frac{\sigma_{g,i}^2}{\mu_{g,i}^2}\right)$, the derivative is **positive**.
- For $\phi > \frac{1}{2}\left(1 + \frac{\sigma_{g,i}^2}{\mu_{g,i}^2}\right)$, the derivative is **negative**.

Figure 7 shows how the expected returns vary as a function of impact probability ϕ in the left-hand panel and the fraction of informed investors q_i in the right-hand panel.

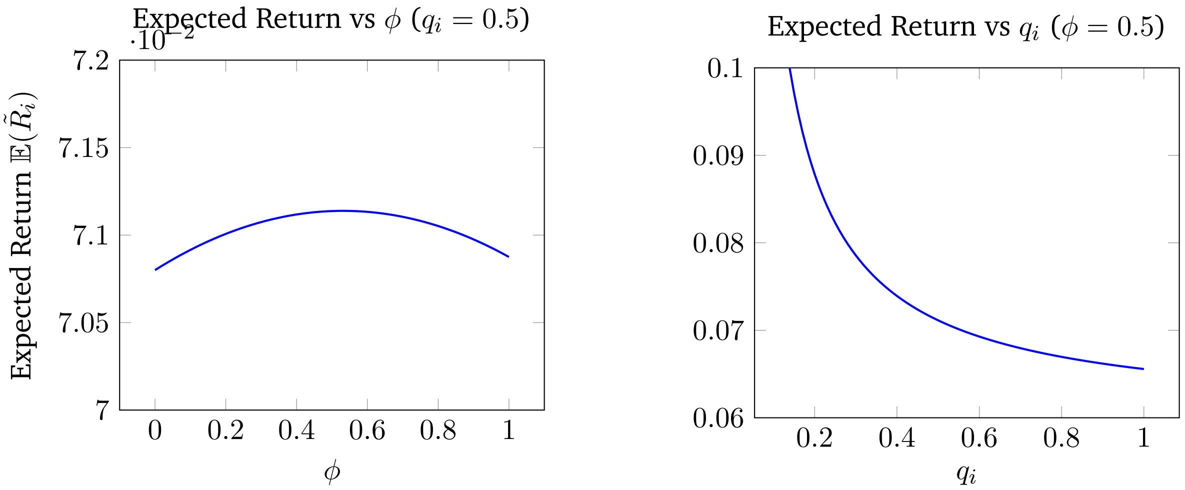
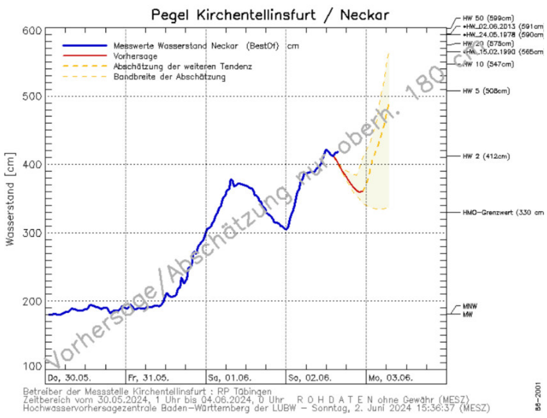


Figure 7. Expected stock return as a function of impact probability ϕ and fraction of informed investors q_i: The left-hand panel shows the humped-shaped impacteffect of the impact probability on the expected returns. The right-hand panel shows how the expected returns increase exponentially if there are more less-informed investors. The following calibration of Eq. (32) is used: $R_f = 0.02$, $b_i = 1$, $R_{K+1} = 0.06$, $3 = 3$, $x_i = 0.02$, $\sigma_i = 0.3$, $\sigma_{g,i} = 0.025$ and $\mu_{g,i} = 0.1$.

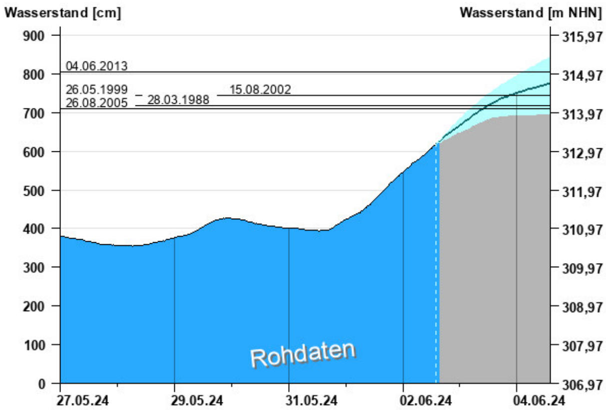
B Early warning signals for storms and floods

(a) Storm Ian: September 23 2022

(b) Storm Ian: September 28 2022



(c) Flood Neckar: June 2 2024



(d) Flood Donau: June 2 2024

Figure 8. An example of early warning systems with storms and floods: In sub-figures (8a) and (8b), we see one of the first and of the last forecasts of hurricane Ian in the US in late September 2022. The predicted area of impact narrows over time and the time-frame of prediction is of around five to seven days. In sub-figures (8c) and (8d), we see the time frame for predicting the water level 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 time frame of prediction is very short, two days max and the uncertainty about the expected water level is very limited. Sources: National Hurricane Center of the US forecast archive, Federal states of Bavaria and Baden-Wuerttenberg.

C Assessing the quality of the matching algorithm

The Extra Tree method achieves a true positive rate of 88% with a relatively low standard deviation (see Table I). In terms of the *F1* score, it ranks as the second-best measure among all models. Extra Tree also demonstrates the highest efficiency for the area under the curve (AUC) across all models that we use. We compare all classification algorithms using the receiver operating characteristic (ROC) curve and AUC, as shown in Figure 9. The classification model performs better when the ROC curve is steeper on the left side of the plot, approaching the point (0,1). Additionally, a higher-performing model features a larger AUC where 0.5 represents a random model, and 1.0 corresponds to perfect classification. In Figure 9, the Adaboost, Gradient Boost, and Random Forest and Extra Tree classifiers have the largest AUC values. Notably, Extra Tree also has the lowest standard deviation across the cross-validation samples.

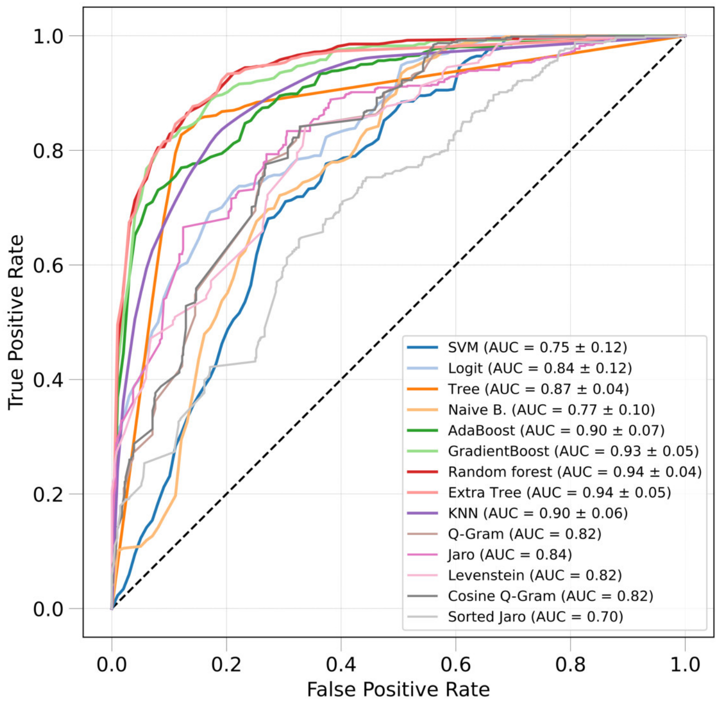


Figure 9. ROC curve of several machine learning models: The figure shows the area under the curve (AUC) for all classification models tested to assess the merging of two company names. The models presented are the linear support vector machine (SVM), logistic regression, the random tree model (Tree), the Naive Bayes classifier, AdaBoost, Gradient Boost, Random Forest, and the Extra Trees classifier, as well as the k-nearest neighbors model. Additionally, we measure the AUC for the similarity measures underlying the machine learning classification models, including Q-Gram, the Jaro-Winkler method, and the Levenshtein measure.

D Boehmer, Musumeci and Poulsen test statistic

We perform a parametric test resilient to event-induced variance, following (Boehmer et al., 1991). These authors compute the abnormal returns (AR) for the cross-sectional dimension of the data. Specifically, they test whether the average abnormal returns (AAR) satisfy the null hypothesis $H_0 : E(AAR) = 0$ by computing the following test statistic:

$$t_B = \frac{1}{N}\sum_{i=1}^{N} SR_{i,t} \Bigg/ \sqrt{\frac{1}{N(N-1)}\sum_{i=1}^{N}\Big(SR_{i,t} - \sum_{i=1}^{N} SR_{i,t}\Big)^2} \tag{34}$$

where:

- i=Company
- N is the number of companies
- t=Event day t in the event window
- $SR_{i,t}$ is the security i's standardized residual on the event day

$$SR_{i,t} = AR_{i,t} \Bigg/ \hat{s}_i \sqrt{1 + \frac{1}{T_i} + \frac{\left(R_{m,E_t} - \bar{R_m}\right)^2}{\sum_{t=1}^{T_i}\left(R_{m,t} - \bar{R_m}\right)^2}} \tag{35}$$

- $R_{m,t}$ market return at event at event day t
- $\bar{R}_m$ average market return during the estimation period
- $\hat{s}_i$ security's i estimated standard deviation of AR_t during the estimation period

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

E Overlaying storms and facilities' to identify affected companies

To identify which companies own facilities in areas that were affected by storms, we combine several databases. For instance, the E-PRTR provides the location of production facilities; Amadeus tracks the ownership structure; Factset offers time series of prices; and the Copernicus Climate Change Service (C3S) dataset on storm indicators for 1979 to 2021 from the Climate Data Store (CDS) from Copernicus, which a service from the European Commission, provides information on windstorm tracks and footprints among others. An overview of how these sources are merged is provided in Figure 10. The figure also highlights the strengths (indicated by a '+') and weaknesses (indicated by a '−') of each source.

From the E-PRTR, we have yearly information about the ownership of facilities. The E-PRTR database provides details on the company name of the direct facility owner, the geographical location, and whether the facility was active between 2008 and 2022. From Amadeus (Bureau van Dijk), we determine whether a company is directly listed on the stock exchange or indirectly

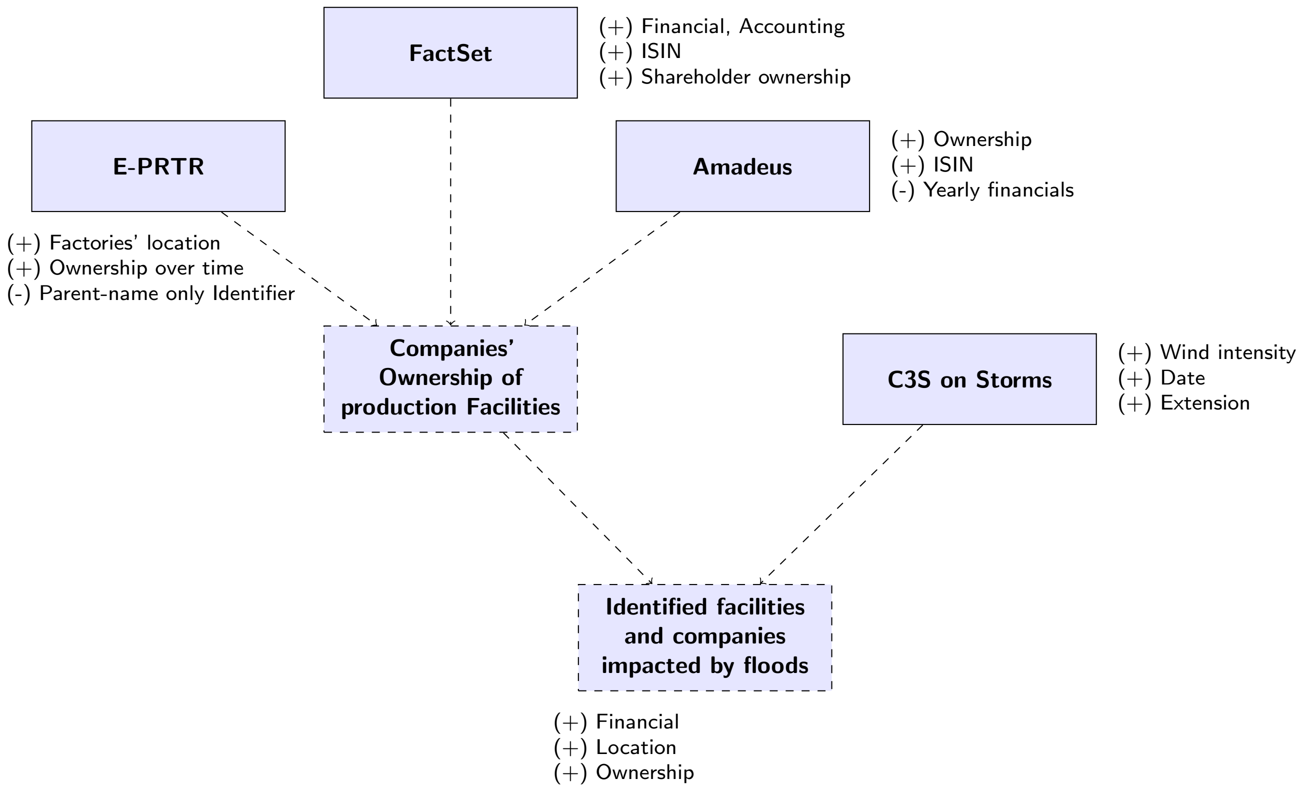


Figure 10. Data sources contributing to the identification strategy: This map illustrates the various data sources that characterize the dataset underlying the analysis. The flood data are sourced from (Brakenridge, 2025), facility locations are obtained from the E-PRTR, and financial data are drawn from Amadeus and Factset. The dotted lines represent merging processes, while the dotted box borders indicate the resulting dataset from a merging process. The strengths (denoted by '+') and weaknesses (denoted by '−') of each source are noted in parentheses.

listed, for example, as a subsidiary of a directly listed company, or as the immediate shareholder (ISH), domestic ultimate owner (DUO), or the global ultimate owner (GUO). Amadeus uses the 50% ownership rule to identify the GUO or the DUO of a company. Additionally, Factset provides information on various components of a company's balance sheet, stock price developments, and market capitalization. Finally, the C3S dataset from Copernicus offers data on the wind intensity date and exact location of 118 major European windstorms that have been identified based on region and simple wind intensity criteria. This total was reached using a 25 m/s threshold.

To identify companies affected by storms, we first merge companies' information from multiple sources (E-PRTR, FactSet, Amadeus) and then geographically join this data with the extent of regions affected by storms. First, we merge the names of facility owners from the E-PRTR on a yearly basis with the names of all companies included in Amadeus. Next, we merge use the ISIN variable from the resulting database in Amadeus with the financial information available in FactSet. The resulting database, which includes the latitude and longitude of each facility, is then overlaid with the extent of regions affected by storms, allowing us to identify which facilities were affected by storms in a given year. Additionally, we geocode the location of company headquarters to compute the distance between facilities and their respective headquarters.

F The sources in detail

Our sample consists of publicly listed European companies that, at the time of a flood, had facilities located in affected regions. Identifying the facilities were affected by extreme weather events is essential to understanding how investors react to such occurrences. The analysis covers facilities in all countries in the European Union (27) as well as Great Britain.

F.a Financial measures

We obtain data on stock prices, market capitalization, and institutional stock ownership from *FactSet Financial Data and Analysis*. The final sample comprises unique publicly listed companies whose facilities were affected by extreme weather events. This sample is extrapolated from a dataset of 3653 daily returns per firm. Financial companies and those with less than a 10% free float are excluded from the analysis.

F.b Facilities

We derive information on the locations of facilities from the E-PRTR. The E-PRTR, as defined in Article 1 of the European Pollutant Release and Transfer Register (E-PRTR), is an integrated pollutant release and transfer register at the community level [...] in the form of a publicly accessible electronic database. It establishes rules for the implementation of the UNECE Protocol on Pollutant Release and Transfer Registers, the facilitation of public participation in environmental decision-making, and its contribution to preventing and reducing environmental pollution.

According to Article 5 of the E-PRTR Regulation, all operators of facilities undertaking one or more activities listed in Annex I of the Regulation must report specific information if they exceed predefined capacity thresholds. These activities cover sectors such as energy; metal production and processing; the mineral and chemical industries; waste and wastewater management; paper and wood production; intensive livestock production and aquaculture; food and beverage production; and other industrial activities. As a result, many companies are required to report their facilities' locations.

The E-PRTR is a public inventory of data submitted by facilities, including information on toxic chemical releases into the air, water, or land; recycling; energy recovery; and off-site transfers for treatment or disposal. A key application of PRTRs is supporting sustainability-related decisions by providing insight into facility-level operations over time. Since 2007, the E-PRTR has expanded significantly and now comprises approximately 94,000 facilities across Europe. However, not every country is covered every year, and the types of reported information vary by country and over time. But, the dataset consistently provides facility locations, ownership details, and waste production amounts. Through our preliminary data merge, we integrate approximately 21,000 unique facility owners and 34,126 unique facilities. Notably, many facility owners are not publicly listed.

The E-PRTR covers various industrial sectors but does not encompass all facilities for every company within these sectors. Facility operators are required to report waste production if their facility's output exceeds predefined capacity thresholds. For example, ferrous metal foundries must report waste production if their capacity exceeds 20 tons per day. However, for some industries, there is no capacity threshold.[20]

F.c The ownership structure of companies

Information on the ownership structure of companies and shareholder holdings is obtained from *Amadeus* by Bureau van Dijk. We track ownership links between subsidiaries and their owners. Amadeus provides data on ultimate ownership and active ownership links. To reconstruct ownership over time, we use the method suggested by (Kalemli-Ozcan et al., 2024) that involves using multiple vintages (point-in-time observations) provided by Amadeus. Across two years (2018 and 2022), we collect approximately 35 million active ownership links. These point-in-time snapshots are assumed to represent the ownership structure for the four years leading up to each snapshot. Specifically, the years 2014 to 2018 are assumed to reflect the ownership structure in 2018 and similarly in 2022.

To analyze how investors react to extreme weather events, we identify ownership links between the E-PRTR facility owner and the closest publicly listed company in terms of ownership

[20] More details on general applications of PRTRs and reporting requirements are available in (OECD, 2017; EPA, 2006).

structure. We take the first publicly listed company in the ownership chain of a facility and compare its location to that of the facility to determine whether they are in the same country. In Amadeus, we use a 50% ownership threshold to declare a company as the ultimate owner of another.

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

Table (VIII) shows the percentage of ownership broken down by ownership category with respect to the location of the facility, security, and security owner. This breakdown is provided for three samples: the E-PRTR facilities successfully linked to securities (“SAMPLE = ALL”), facilities affected by storms (“SAMPLE = STORM”), and facilities affected by floods (“SAMPLE = FLOOD”).

"Home" refers to the country of the company issuing the security. Depending on the location of the facility or the institutional security owner (IO), these may be in different regions abroad or share the same location as the security. For example, if the IO, security, and affected facility are all located in the same country, the corresponding column in the table will be labeled *“LIO”*. If the IO and security are based in the local country while the affected facility is abroad, the column will be labeled *“A(F)”*. If the affected facility and the security owner are located in two different countries abroad, the column will be labeled *“A (IO<>F)”*.

Table (VIII) shows that there is sufficient geographical ownership variation in the sample. For 50% of the facilities, the owner and the traded security linked to them are located in the US. Comparing the three samples presented in Table (VIII), we do not find significant differences among them.

LIO Country	ALL: LIO	ALL: A(IO<>F)	ALL: A (I=F)	ALL: A (IO)	ALL: A (F)	WIND: H	WIND: A (IO<>F)	WIND: A (IO=F)	WIND: A (IO)	WIND: A (F)	FLOOD: H	FLOOD: A (IO<>F)	FLOOD: A (IO=F)	FLOOD: A (IO)	FLOOD: 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 divided into six groups to ease visualisation. When the affected facility, security, and IO share the same country, then they belong to "LIO". When affected facility and security but IO share the same country they belong to "A (IO)". 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 (IO=F)". Finally, when security is home but IO and affected facility are two different countries they belong to "A (IO<>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 Storms

We compute the exposure of companies to storms in Europe using the storm footprints from the Climate Data Store, provided by the Copernicus Programme.[21] The dataset provides climatological indicators on European storms and their economic impact, derived from ERA5 reanalysis. We focus on storm footprints, defined as the maximum 3-second 10-m wind gust speed in meter per second (m/s) over a 72-hour period at each model grid point for significant storms. A storm footprint thus 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 storms, provided 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 exceed the selection criteria threshold of 25 m/s 10-m winds over land, using a 3-degree sampling region. As a result, our sample does not include data for the years 2018 and 2019. Due to the timeframe considered in our analysis, we only include storm footprints from 2014 to 2021. Figure 11 shows all areas and the relative storm speed of all storms that affected Europe from 2014 to 2021. In sub-figure 11b, we show the footprint of Storm Ciara, which affected Europe from February 7 to February 11, 2020, and had particularly damaging effects on the affected areas.

(a) Storms (2014-2021)

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

Figure 11. storms in Europe from 2014 to 2021: In sub-figure (11), we show the areas and intensity of storms that affected Europe from 2014 to 2021. In sub-figure (11b), we show the area that was affected by Storm Ciara from 7 to 11 February 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.

Our sample consists of 16 storms, which are heterogeneously distributed throughout Northern

[21] More information can be found under Copernicus Programme.

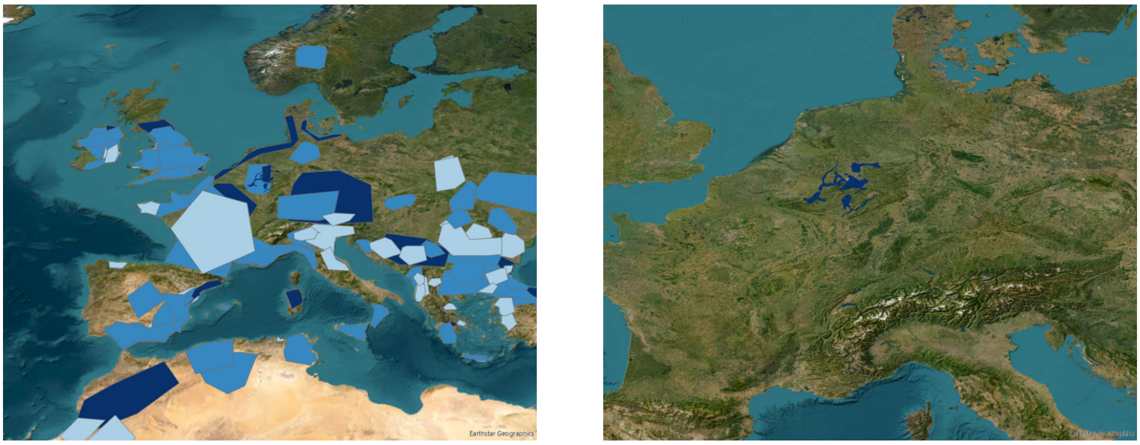
Europe as shown in Figure (11). The average historical the maximum 3-second 10m wind gust over time and events is 34 m/s. A windspeed of above 30 m/s is considered to be damaging for most European buildings (Prahl et al., 2016) . The event date is the day of the weather's landfall as suggested in (Lanfear et al., 2019).

F.f Floods

To compute the exposure of companies to floods, we use information in form of polygons provided by Brakenridge (2025). The database provides global coverage of the strongest flood events to have occurred in history and an estimate of the land surface affected. The severity of the floods is measured through the Severity Class assessment on a 1 to 2 scale. The floods are divided into three severity classes. Class 1 events are large floods that caused significant damage to structures, agriculture, fatalities, and/or featured a 1 to 2 decades long reported interval since the last similar event. Class 1.5 contains very large events with an interval of greater than 2 decades but less than 100 year between occurrences, a local recurrence interval of 1 to 2 decades and having affected a large geographic region (e.g. $>$ 5000 sq. km). Class 2 contains extreme events with an estimated recurrence interval greater than 100 years.

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

Our flood sample consists of 68 flood events. Some 35 events have a severity class of 1.5, 27 have a severity of 1.0, and 6 have a severity class of 2.0.The geographic distribution of events is very heterogeneous. Figure (12) shows that most of the events take place in Central and Southern Europe. Specifically, 10 occurred in Spain as the main country, 8 in Italy, 10 in France, 7 in Greece, and 5 in Great Britian. Sub-figure (12b) gives a picture of the case study on the summer floods in Belgium, Germany, and the Netherlands in July 2021, which affected several regions. The event is classified as being in severity class 2.



(a) Floods (2014-2021) (b) Floods (13 - 15 Jul 2021)

Figure 12. Floods in Europe from 2014 to 2021: In sub-figure (12), we show the areas and severities of floods that affected Europe from 2014 to 2021. In sub-figure (12b), we show the area that was affected by the summer floods in the Belgium, Germany, and the Netherlands in July 2021. The different colors show different levels of severity by polygon. The darker the lower the recurrence interval of that flood event in the area.

G Additional Results

G.a Cumulative average abnormal returns over years and event types

Our results are persistent over time and are not driven by a specific outlier year, such as the year when Covid lockdowns were announced. In Table (IX), the horizontal axis shows the CAAR averaged over the course of a year, while the vertical axis shows the results for different event window buckets, broken down by weather-related event type. Table (IX) demonstrates that, after the event, CAAR is negative and significantly different from zero for each year. The only exceptions to this result are 2016 for storms, and 2014, 2015, and 2018 for floods. Additionally, we find that the results are consistently larger for 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 storms and floods aggregated over the days from the event by year of occurrence and the Mkt estimation models to estimate the 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 determined that the sectors of manufacturing, utility, water, and mining were the ones that were highly exposed to climate hazards of different types. These sectors are highly represented in the sample we matched with the E-PRTR. The manufacturing sector is 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 affected. In Table (X) we provide an overview of the facilities affected by extreme weather events as a percentage of the whole sample.

	All companies			Listed companies		
	Affected	Total	% Total	Affected	Total	% Total
ADMINISTRATIVE	570	1163	1.78	52	90	1.29
AGRICULTURE	282	904	0.88	10	31	0.25
COMMUNICATION	99	233	0.31	18	44	0.45
CONSTRUCTION	356	762	1.11	18	46	0.45
EDUCATION	11	16	0.03	NaN	NaN	NaN
ENTERTAINMENT	27	69	0.08	1	1	0.02
FINANCIAL	446	798	1.39	34	82	0.85
HEALTH	537	1291	1.68	NaN	NaN	NaN
MANUFACTURING	7412	15488	23.14	766	1972	19.05
MINING	172	501	0.54	92	287	2.29
OTHER	116	207	0.36	42	52	1.04
PUBLIC	141	242	0.44	8	8	0.20
REAL ESTATE	322	634	1.01	3	6	0.07
SALES	1002	2221	3.13	67	170	1.67
SERVICE	76	159	0.24	1	1	0.02
TECHNICAL	530	1122	1.65	46	110	1.14
TRANSPORTATION	216	515	0.67	33	67	0.82
UTILITIES	575	1427	1.80	179	455	4.45
WATER	1965	4274	6.14	337	599	8.38
Total	14855	32026	46.38	1707	4020	42.46

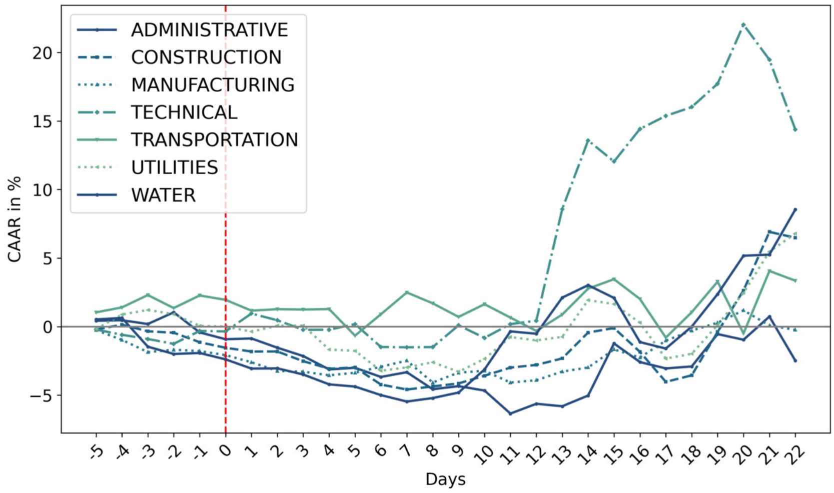
Table X. Affected facilities by NACE category from 2014-2021 for all hazards: In this table, we show the number of unique facilities for which we could follow the ownership structure by NACE category. In the first 3 columns we show the affected facilities, the total number of facilities we match, and the percentage of facilities affected, with a 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 13, we report the CAAR for Storm Ciara and we see that it is mostly negative and persistent over a longer period for three main NACE categories: Construction, Manufacturing, and Water.[22]

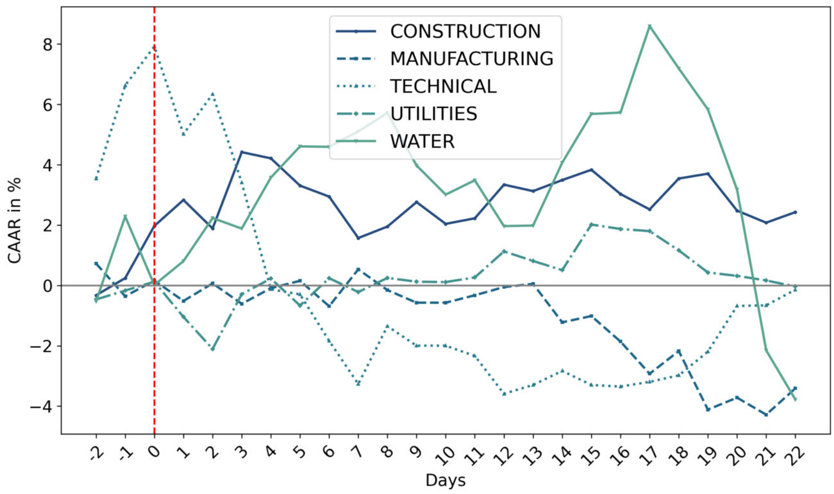
In Figure (14a), we report the results of the case study for the summer floods in norther Europe in summer 2021. After a breakdown by economic activity, we find that manufacturing or professional, scientific, and technical activities are negatively affected by floods.

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



(a) Ciara

Figure 13. CAAR for Storm Ciara February 2020 by Industry: In Figure (13), we depict CAAR broken down by NACE economic section for companies affected by Storm Ciara which formed on 10 February 2020 and dissipated on 16 February 2020. The Y-axis of each figure represents the CAAR in %, and the X-axis days from the event, where positive values are after event beginning and negative before.

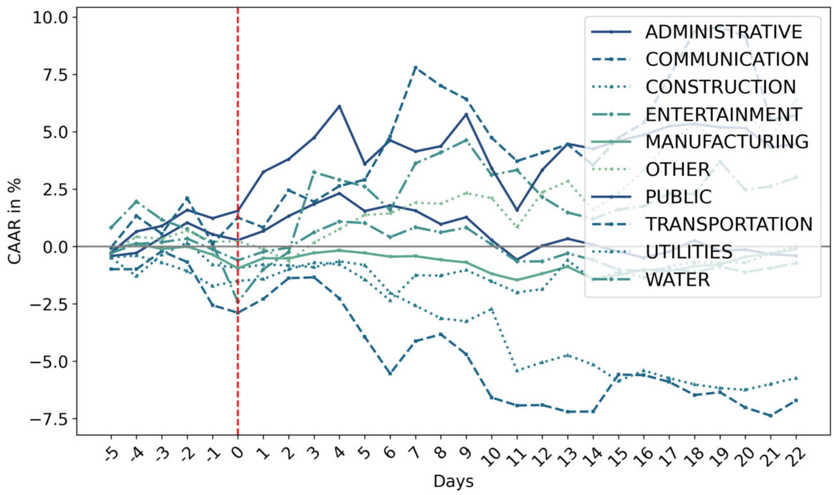


(a) Floods July 2021

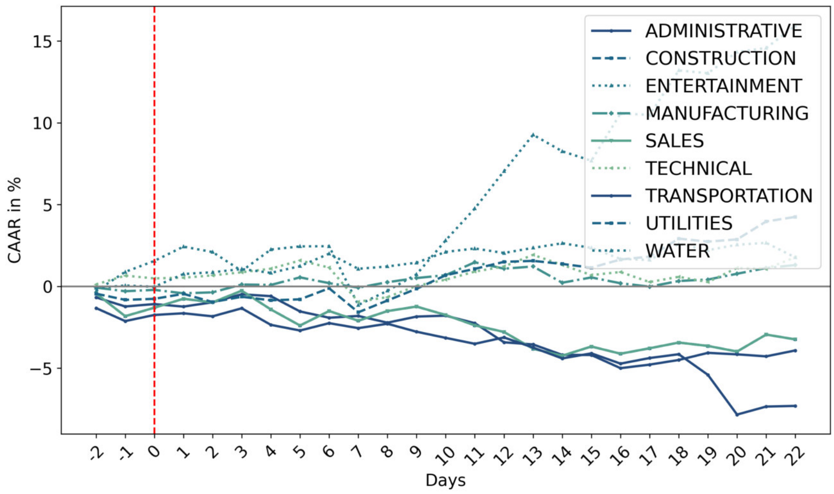
Figure 14. CAAR for the summer floods in Central Europe July 2021: In Figure (14), we compute the CAAR broken down by NACE economic section for companies affected by the summer floods in Germany, Belgium, and the Netherlands from 13 to 15 July 2021. The Y-axis of each figure represents the CAAR in %, and the X-axis days from the event, where positive values are after the event's start and negative before.

H.a.1 The whole sample

Next, we analyse whether the industry of affected companies influences investors' reaction. Specifically, we expect to see a stronger reaction for an industry that has a material exposure to physical risks. For instance those highlighted in the (Dunz et al., 2021), such as manufacturing and construction.



(a) STORMS



(b) FLOODS

Figure 15. Cumulative Average Abnormal Returns (CAAR) by event type: In sub-figures (15a and 15b), we depict the CAAR broken down by NACE economic section for companies affected by storms and floods. The Y-axis of each figure represents the CAAR in %, and the X-axis days from the event, where positive values are after the event's start and negative before.

Sub-figure (15a) shows that the industries that are mostly affected are manufacturing, utilities, construction, and transportation. Sub-figure (15b) shows that transportation related activities suffer the most from floods.

I Replicating the analysis with the 3F, 4F and 5F

	$CAR_{t,3F}$					
	STORM			FLOOD		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
β_0	0.4781**	0.4764**	1.8479***	0.1978	0.3258*	0.3135
	(0.1899)	(0.1910)	(0.3936)	(0.2224)	(0.1980)	(0.4070)
LIO_{t-1}	0.0091***	0.0032	0.0034	0.0022	-7.87e-05	0.0077
	(0.0022)	(0.0034)	(0.0095)	(0.0027)	(0.0031)	(0.0084)
$Post_t$	-3.4715***	-2.8299***	-4.4040***	-0.5805**	-0.7356***	-0.8193
	(0.2432)	(0.2644)	(0.6138)	(0.2664)	(0.2594)	(0.5486)
$LIO_{t-1} \cdot Post_t$	0.0223***	0.0123***	0.0948***	0.0049	0.0083*	-0.0061
	(0.0030)	(0.0047)	(0.0143)	(0.0042)	(0.0048)	(0.0106)
EAL_i		-50.768**			-0.0471	
		(25.178)			(0.0290)	
$LIO_{t-1} \cdot EAL_i$		2.6674**			0.0012**	
		(1.3012)			(0.0005)	
$Post_t \cdot EAL_i$		-178.19***			0.0636*	
		(35.137)			(0.0351)	
$LIO_{t-1} \cdot Post_t \cdot EAL_i$		4.2143***			-0.0021***	
		(1.4971)			(0.0007)	
$ln(Dist_i)$			-0.2352***			-0.0229
			(0.0480)			(0.0520)
$LIO_{t-1} \cdot ln(Dist_i)$			0.0012			-0.0007
			(0.0012)			(0.0012)
$Post_t \cdot ln(Dist_i)$			0.1323			0.0480
			(0.0818)			(0.0725)
$LIO_{t-1} \cdot Post_t \cdot ln(Dist_i)$			-0.0095***			0.0013
			(0.0018)			(0.0016)
N	5,593	5,593	5,593	14,022	14,022	14,022
R^2	0.0262	0.0476	0.0482	0.0018	0.0024	0.0024
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Table XI. Regression of $CAR_{3F,i,t}$ on $LIO_{i,t-1}$ and $EAL_i, ln(Dist_i)$: In Table (XI), we show the fixed effects regression where $CAR_{it,Mkt}$ is the dependent variable. The explanatory variables are: $LO_{(i,t-1)}$ or the quarterly lagged percentage of LIO calculated using the measure by Coeurdacier and Rey (2013) and definitions from Coval and Moskowitz (2001), EAL_i or the expected annual loss. $Post_t$ which is a dummy equal to one for the days at or after the event and [$ln(Dist_i)$, which is the logarithm of the distance in kilometers between the facility and the headquarters as suggested in (Pellegrino et al., 2024)]. Covariance is clustered by time (Petersen, 2009). N is the number of $CAR_{t,Mkt}$ by day and company over which regressions are computed.

	$CAR_{t,4F}$					
	STORM			FLOOD		
	(1)	(2)	(3)	(1)	(2)	(3)
β_0	0.1866	0.1769	1.4310***	0.2267	0.3975	-0.1230
	(0.2790)	(0.2856)	(0.3924)	(0.3105)	(0.2870)	(0.4760)
LIO_{t-1}	0.0127***	0.0061*	0.0078	0.0019	-0.0010	0.0124
	(0.0018)	(0.0034)	(0.0095)	(0.0030)	(0.0035)	(0.0089)
$Post_t$	-2.9088***	-2.3284***	-3.5680***	-0.8324**	-1.0226***	-1.3633**
	(0.3431)	(0.3571)	(0.6396)	(0.3630)	(0.3574)	(0.6333)
$LIO_{t-1} \cdot Post_t$	0.0199***	0.0116**	0.0922***	0.0039	0.0079	-0.0047
	(0.0026)	(0.0045)	(0.0138)	(0.0046)	(0.0054)	(0.0115)
EAL_i		-48.049*			-0.0605*	
		(26.994)			(0.0313)	
$LIO_{t-1} \cdot EAL_i$		2.9374**			0.0014***	
		(1.3805)			(0.0005)	
$Post_t \cdot EAL_i$		-156.54***			0.0757*	
		(36.378)			(0.0387)	
$LIO_{t-1} \cdot Post_t \cdot EAL_i$		3.5388**			-0.0024***	
		(1.6036)			(0.0008)	
$ln(Dist_i)$			-0.2152***			0.0565
			(0.0451)			(0.0572)
$LIO_{t-1} \cdot ln(Dist_i)$			0.0010			-0.0015
			(0.0012)			(0.0013)
$Post_t \cdot ln(Dist_i)$			0.0879			0.0962
			(0.0853)			(0.0789)
$LIO_{t-1} \cdot Post_t \cdot ln(Dist_i)$			-0.0094***			0.0009
			(0.0018)			(0.0018)
N	5,593	5,593	5,593	14,022	14,022	14,022
R^2	0.0268	0.0428	0.0499	0.0012	0.0019	0.0031
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Table XII. Regression of $CAR_{4F,i,t}$ on $LIO_{i,t-1}$ and $EAL_i, ln(Dist_i)$: In Table (XII), we show the fixed effects regression where $CAR_{it,Mkt}$ is the dependent variable. The explanatory variables are: $LO_{(i,t-1)}$ or the quarterly lagged percentage of LIO calculated using the measure by Coeurdacier and Rey (2013) and the definitions from Coval and Moskowitz (2001), EAL_i or the expected annual loss. $Post_t$ which is a dummy equal to one for the days at or after the event and [$ln(Dist_i)$, which is the logarithm of the distance in kilometers between the facility and the headquarters as suggested in (Pellegrino et al., 2024)]. Covariance is clustered by time (Petersen, 2009). N is the number of $CAR_{t,Mkt}$ by day and company over which regressions are computed.

	$CAR_{t,5F}$					
	STORM			FLOOD		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
β_0	0.5547***	0.5943***	2.2054***	0.0507	0.2030	0.0289
	(0.1888)	(0.1963)	(0.5024)	(0.2138)	(0.1937)	(0.3960)
LIO_{t-1}	0.0073***	-0.0013	0.0035	0.0021	-0.0003	0.0088
	(0.0027)	(0.0034)	(0.0088)	(0.0029)	(0.0033)	(0.0078)
$Post_t$	-3.4155***	-2.7196***	-2.8168***	-0.3670	-0.4652*	-0.3777
	(0.2403)	(0.2667)	(0.6772)	(0.2577)	(0.2541)	(0.5361)
$LIO_{t-1} \cdot Post_t$	0.0219***	0.0108**	0.0794***	0.0016	0.0040	-0.0131
	(0.0036)	(0.0051)	(0.0140)	(0.0043)	(0.0048)	(0.0101)
EAL_i		-82.728***			-0.0522*	
		(22.728)			(0.0281)	
$LIO_{t-1} \cdot EAL_i$		3.8640***			0.0011**	
		(1.1432)			(0.0005)	
$Post_t \cdot EAL_i$		-181.06***			0.0419	
		(31.492)			(0.0338)	
$LIO_{t-1} \cdot Post_t \cdot EAL_i$		4.7448***			-0.0017**	
		(1.3459)			(0.0007)	
$ln(Dist_i)$			-0.2837***			0.0012
			(0.0681)			(0.0541)
$LIO_{t-1} \cdot ln(Dist_i)$			0.0010			-0.0009
			(0.0012)			(0.0012)
$Post_t \cdot ln(Dist_i)$			-0.1049			0.0095
			(0.0951)			(0.0743)
$LIO_{t-1} \cdot Post_t \cdot ln(Dist_i)$			-0.0071***			0.0019
			(0.0019)			(0.0016)
N	5,593	5,593	5,593	14,022	14,022	14,022
R^2	0.0220	0.0475	0.0543	0.0005	0.0013	0.0011
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Table XIII. Regression of $CAR_{5F,i,t}$ on $LIO_{i,t-1}$ and $EAL_i, ln(Dist_i)$: In Table (XIII), we show the fixed effects regression where $CAR_{it,Mkt}$ is the dependent variable. The explanatory variables are: $LO_{(i,t-1)}$ or the quarterly lagged percentage of LIO calculated using the measure by Coeurdacier and Rey (2013) and the definitions from Coval and Moskowitz (2001), EAL_i or the expected annual loss. $Post_t$ which is a dummy equal to one for the days at or after the event and [$ln(Dist_i)$, which is the logarithm of the distance in kilometers between the facility and the headquarters as suggested in (Pellegrino et al., 2024)]. Covariance is clustered by time (Petersen, 2009). N is the number of $CAR_{t,Mkt}$ by day and company over which regressions are computed.

J Robustenss tests: excluding the US and year 2020

	$CAR_{t,Mkt}$ w/o the United States					
	STORM			FLOOD		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
β_0	-0.5332	-0.5538*	0.4010	0.1966	0.2437	0.7049*
	(0.3504)	(0.3323)	(0.5755)	(0.2366)	(0.2313)	(0.4153)
LIO_{t-1}	0.0153***	0.0145***	0.0255**	0.0076**	0.0068*	-0.0049
	(0.0032)	(0.0043)	(0.0099)	(0.0033)	(0.0037)	(0.0078)
$Post_t$	-2.4516***	-1.8738***	-3.8120***	-0.7985***	-0.9432***	-0.6386
	(0.4492)	(0.4545)	(0.7458)	(0.2863)	(0.2928)	(0.5619)
$LIO_{t-1} \cdot Post_t$	0.0366***	0.0233***	0.1111***	0.0074*	0.0131**	-0.0096
	(0.0041)	(0.0052)	(0.0141)	(0.0044)	(0.0051)	(0.0103)
EAL_i		-0.0977			-0.0148	
		(20.473)			(0.0314)	
$LIO_{t-1} \cdot EAL_i$		0.4867			0.0003	
		(1.0974)			(0.0007)	
$Post_t \cdot EAL_i$		-200.44***			0.0729**	
		(34.537)			(0.0369)	
$LIO_{t-1} \cdot Post_t \cdot EAL_i$		5.5407***			-0.0039***	
		(1.3211)			(0.0009)	
$ln(Dist_i)$			-0.1486**			-0.0879
			(0.0641)			(0.0558)
$LIO_{t-1} \cdot ln(Dist_i)$			-0.0019			0.0022
			(0.0014)			(0.0014)
$Post_t \cdot ln(Dist_i)$			0.2548***			-0.0290
			(0.0897)			(0.0776)
$LIO_{t-1} \cdot Post_t \cdot ln(Dist_i)$			-0.0128***			0.0031*
			(0.0020)			(0.0018)
N	4,557	4,557	4,557	12,270	12,270	12,270
R^2	0.0406	0.0582	0.0644	0.0048	0.0097	0.0077
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Table XIV. Regression of $CAR_{Mkt,i,t}$ on $LIO_{i,t-1}$ and $EAL_i, ln(Dist_i)$: In Table (XIV), we show the fixed effects regression where $CAR_{it,Mkt}$ is the dependent variable. The explanatory variables are: $LO_{(i,t-1)}$ or the quarterly lagged percentage of LIO calculated using the measure by Coeurdacier and Rey (2013) and the definitions from Coval and Moskowitz (2001), EAL_i or the expected annual loss. $Post_t$ which is a dummy equal to one for the days at or after the event and [$ln(Dist_i)$, which is the logarithm of the distance in kilometers between the facility and the headquarters as suggested in (Pellegrino et al., 2024)]. Covariance is clustered by time (Petersen, 2009). N is the number of $CAR_{t,Mkt}$ by day and company over which regressions are computed.

	$CAR_{t,Mkt}$ the year 2020					
	STORM			FLOOD		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
β_0	-0.0140	0.0640	1.6584**	0.3353	0.3892*	0.3993
	(0.2785)	(0.3549)	(0.7220)	(0.2364)	(0.2255)	(0.4193)
LIO_{t-1}	0.0116***	-0.0069	0.0016	0.0019	0.0005	0.0038
	(0.0022)	(0.0049)	(0.0161)	(0.0027)	(0.0031)	(0.0078)
$Post_t$	-2.1879***	-2.5233***	-4.6318***	-0.6651**	-0.7862***	-1.1663**
	(0.3457)	(0.5205)	(0.9570)	(0.2856)	(0.2890)	(0.5664)
$LIO_{t-1} \cdot Post_t$	0.0203***	0.0330***	0.1181***	0.0029	0.0058	0.0043
	(0.0032)	(0.0074)	(0.0205)	(0.0038)	(0.0045)	(0.0104)
EAL_i		-240.65**			-0.0240	
		(102.94)			(0.0297)	
$LIO_{t-1} \cdot EAL_i$		9.0990***			0.0008	
		(1.7440)			(0.0005)	
$Post_t \cdot EAL_i$		469.44***			0.0528	
		(173.79)			(0.0351)	
$LIO_{t-1} \cdot Post_t \cdot EAL_i$		-7.0239***			-0.0018**	
		(2.4778)			(0.0007)	
$ln(Dist_i)$			-0.2803***			-0.0129
			(0.0996)			(0.0521)
$LIO_{t-1} \cdot ln(Dist_i)$			0.0018			-0.0002
			(0.0021)			(0.0011)
$Post_t \cdot ln(Dist_i)$			0.3516***			0.0875
			(0.1336)			(0.0735)
$LIO_{t-1} \cdot Post_t \cdot ln(Dist_i)$			-0.0126***			-0.0004
			(0.0027)			(0.0015)
N	4,445	4,445	4,445	13,615	13,615	13,615
R^2	0.0313	0.0430	0.0582	0.0010	0.0016	0.0014
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Table XV. Regression of $CAR_{Mkt,i,t}$ on $LIO_{i,t-1}$ and $EAL_i, ln(Dist_i)$: In Table (XV), we show the fixed effects regression where $CAR_{it,Mkt}$ is the dependent variable. The explanatory variables are: $LO_{(i,t-1)}$ or the quarterly lagged percentage of LIO calculated using the measure by Coeurdacier and Rey (2013) and the definitions from Coval and Moskowitz (2001), EAL_i or the expected annual loss. $Post_t$ which is a dummy equal to one for the days at or after the event and [$ln(Dist_i)$, which is the logarithm of the distance in kilometers between the facility and the headquarters as suggested in (Pellegrino et al., 2024)]. Covariance is clustered by time (Petersen, 2009). N is the number of $CAR_{t,Mkt}$ by day and company over which regressions are computed.

Acknowledgements

We express our gratitude to Nuvolos for providing access to high-performance computing clusters through a PhD fellowship, and to Inquire Europe for financially supporting our research. We also thank the 3rd GIGS and the 7th SIIC conferences for our best paper award. Special thanks to our discussants, Oliver Huber, Nadia Massoud, and Jolie Noels; and to the participants of the ECB Climate Change Centre Green Seminar Series, Oxford Spatial Finance initiative seminar, the Geneva Brown bag seminar, the 3rd workshop from the ESCB Climate Change Research Cluster, the 7th GRASFI, the 3rd GIGS, the 16th SoFiE, the 17th Financial Risks International Forum, and the 7th SIIC conferences as well as GRASFI's PhD workshop, the SoFiE Financial Econometrics Summer School on 'Climate Finance,' the 3rd Summer School on Advanced Economics, MORSE, the SoFiE European Summer School. We are also grateful to Maastricht University's Finance Department, and to Dennis Bams, Marco Ceccarelli, Peter Schotman, Dieter Wang and Francesco Mongelli for their valuable feedback.

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PDF ISBN 978-92-899-7378-6 ISSN 1725-2806 doi:10.2866/8995136 QB-01-25-153-EN-N