Stormy Investments: Navigating Preferences and Barriers in Weather Disasters

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February 17, 2024

Abstract

In this event study, we exploit Geographic Information Systems (GIS) to show that weather-related disasters negatively surprise equity investors under informational frictions. We determine the exposure of firms to weather-related disasters by overlaying the locations of production facilities with geographic regions affected by hazards. We complement this data with firms' financial information, the ownership structure of the facilities, investors' ownership of companies, and disasters' vulnerability on a facility level. For winter windstorms, we find a negative cumulative average risk-adjusted abnormal daily return of 99 basis points at the event date. Furthermore, if the firm's impacted facility is located abroad with respect to the firm's headquarters, the negative impact on stock returns reaches up to 139 basis points. The magnitude of the negative surprise is reduced in two cases: i) when the impacted facilities are located in the home country of the publicly listed firm's headquarters ; ii) for those companies whose institutional investors' base features home equity investment preference. We base our findings on a sample of 600 unique companies, 1,748 facilities, 68 floods, 16 winter storms, and 2,332 wildfires from 2014 to 2021. Our results are statistically and economically significant for investors.

JEL: Q54; G11; G14; G32; C81;

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[§]Acknowledgments: We express our gratitude to Nuvolos for providing us access to high computing clusters with a PhD fellowship, Inquire Europe for financially supporting our research, the participants of the 7th SIIIC conference, GRASFI PhD workshop, the SoFiE Financial Econometrics Summer School on "Climate Finance",the SoFiE European Summer School, Maastricht's Finance Department, Dennis Bams, Dieter Wang and Marco Ceccarelli for their feedback.

Introduction

The recent Global Risks Report by the World Economic Forum shows "a world plagued by a duo of dangerous crises: climate and conflict" (World Economic Forum, 2024). Two risks are in the top five risks for the short and long term: "Extreme weather events" and "Misinformation and disinformation". Changes in precipitation already impact the life of 85% of the world's population and the Bank of International Settlements (BIS) estimates that weather-related natural disasters caused $ 3 trillion losses from 1980 and 2018. The European Environment Agency (EEA) attributes € 560 billion of these losses to the EU in the same time span (Basel Committee on Banking Supervision, 2021; IPCC, 2021; Callaghan et al., 2021; Ridder et al., 2022).[1] In the current international political environment dominated by trade barriers and political conflicts, we investigate how weather-related disasters impact asset prices under market segmentation and informational barriers.

We analyse the impact of weather related disasters (e.g., winter windstorms, wildfires, and floods) on stock prices matching information on production facilities, stock ownership and weather related disasters. To do so, we investigate the role of informational distance (e.g., whether a facility is located abroad compared to the headquarters), investors' home equity preference, and facilities' vulnerability to weather-related disaster risk in shaping financial markets reactions. We think that market reactions are influenced by the information assumption, which captures the idea that while foreigners may see home information as well as home residents, they do not know how to interpret it.[2] We expect this assumption to hold also for weather-related disasters, a yet underinvestigated risk for investors.

By exploring the impact of weather-related disasters on investors' returns under investment frictions, we contribute to several research strains. First, we add to the literature that analyses the impact of weather-related disasters on stocks by investigating how the impact of these shocks is amplified by uncertainty and informational barriers (Kruttli et al., 2023; Alok et al., 2020; Braun et al., 2021; Le Guenedal et al., 2021; Lanfear et al., 2019; Hong et al., 2019). Second, we analyse the role and impact of informational barriers and investor biases on the investor reaction to weather-related disasters. Our work provides additional empirical evidence for the theoretical work on information barriers and investment bias (Pellegrino et al., 2022; Ferreira et al., 2017b; Jia et al., 2017; Dumas et al., 2017). In addition, we contribute to the investigation of home equity preference in Europe, a region prone to this bias (Boermans and Galema, 2023; Coeurdacier and Rey, 2013; Ferreira et al., 2017a). Third, by combining information on facilities, weather-related disasters, ownership and financial using a fuzzy-match algorithm and spatial geographical joins, we contribute to the literature using granular location data to assess the impact of weather-related disasters on stocks (Bressan et al., 2022; Huynh and Xia, 2021). Fourth, we provide one the first implementations of E-PRTR facility

[1] Source: Economic losses from climate-related extremes in Europe (8th EAP), EEA, 21 April 2023.
[2] Assuming that investors start history with prior beliefs that ignore the relationships between the signals and the expected growth rates, and gradually discover them as data come in (Pellegrino et al., 2022; Dumas et al., 2017).

data for the analysis of physical risk, thus adding to the literature using this source for the analysis of climate risk (Germeshausen and von Graevenitz, 2022). Finally, we analyse an innovative regional framework together with particularly relevant and under-investigated hazards (EIOPA, 2022). Winter storms, wildfires, and floods are strongly affecting Europe and have a high economic relevance for the region.[3]

With our empirical analysis we investigate how theories on the impact of uncertainty and informational barriers on asset prices hold during weather-related disasters (Kruttli et al., 2023; Pellegrino et al., 2022; Bansal et al., 2021). We study the following question: To what extent does investors' reaction to weather-related disasters depend on the type of disaster, investor informational distance, and investing preferences? To answer this question, we focus on developed economies with the intention of raising awareness of the disruptions that weather-related disasters cause in the financial markets of developing countries. To do so, we follow to the best of our knowledge two methodologies: one on the impact of physical risk on stocks (Bressan et al., 2022) and one on the calculation of physical risk indicators (Statistics Committee of the ESCB, 2023). Furthermore, by working with publicly available databases provided by the European Commission, we investigate the strengths and weaknesses of these data sources for economic analysis, thus providing knowledge on their suitability on adaptation to climate change tasks (European Commission, 2021).

We implement an innovative empirical setting characterised by three pillars. First, the spatial identification of companies affected by weather-related disasters using the geographical location of the production facilities. Second, the historical reconstruction of the ownership of the facilities. Third, we show that the spatial identification method has an intrinsic forward-looking nature.The pillars interact as follows. We overlay the location of the production facilities and the region impacted by the hazards to detect historically affected companies .[4] We investigate the ownership structure of the facilities to detect the closest public listed company in the ownership chain. Finally, to understand whether investors already update their expectations before, at, or after the event we compute the risk-adjusted abnormal returns around the event dates based on stock prices of the facilities' closest public listed companies.

We implement an event-study methodology with a focus on Europe, that exploits data provided by European institutions. We identify companies impacted by weather-related disasters linking the disaster area with the location of facilities provided by the European Pollutant Release and Transfer Register (E-PRTR). We record the area and disaster related variables for floods from the Darthmouth Flood Observatory (DFO) (Brakenridge, 2021), together with historical data on winter wind storms and wildfires from the *"Climate Data*

[3] For more information on impact of climate change in Europe, look at Fragile State Index (FSI) and (Kemp et al., 2022)

[4] An overlay is a procedure that estimates the attributes of one or more features by superimposing them over other features, and figuring out the extent to which they overlap. You use overlays to estimate the attributes of features in a map layer based on data in another map layer. We follow this practice, which is commonly called *"spatial finance"* and is a field that has significant potential to help improve transparency and accountability (McCarten et al., 2021; Patterson et al., 2020, 2022; Eberenz et al., 2020).

Store" of the European Commission. We then develop a fuzzy string matching algorithm, to merge E-PRTR facility owner names with Orbis companies' ownership structures, thus linking facilities with the closest publicly listed company in the ownership structure.[5] With this information, we compute risk-adjusted cumulative abnormal returns during the event using Factset's daily stock prices. We investigate the validity of the applied methodology, providing a case study analysis for winter windstorm Ciara in February 2020, the wildfires in Portugal from June to October 2017 and the July 2021 river floods in Germany, Belgium and the Netherlands.[6] We implement a typical event study approach for all events from 2022 to 2014 following guidelines developed in the literature (Barnett, 2023; Koijen et al., 2016; Kolari and Pynnönen, 2010; MacKinlay, 1997). To compute abnormal returns, we use the most established factor models (Fama and French, 1993; Carhart, 1997; Fama and French, 2015, 2018) and test for the significant difference with actual returns using robust parametric (Boehmer et al., 1991) and non-parametric (Corrado, 1989) cross-sectional variance measures.

With this approach we have three main findings. First, our results lead to similar findings for winter windstorms for the sign and magnitude of abnormal returns as in Kruttli et al. (2023). However, for floods and wildfires, we do not find strong evidence suggesting repricing as in Huynh and Xia (2021). For floods, investors do not update their beliefs about ESG for different levels of flood exposure, as they appear to be indifferent to flood risk as shown by Giglio et al. (2023); however, the existence of state insurance policies in several European countries for floods and wildfires influences investors' risk perception (EIOPA, 2022). Second, when the affected company has an investor base with a preference to invest in their home country then cumulative average abnormal returns are less strong compared to other companies. This result is explained by home investors having more time to study the relationship between the risk of weather disaster and the company due to local knowledge and language advantage. Alternatively, foreign investors may consider it too costly to access the same information as home investors. Different investors reactions are dependent on the direction and perception of the signal by investors home and abroad(Pellegrino et al., 2022; Coeurdacier and Rey, 2013). Third, we find that investors are more negatively surprised by the event if the companies' vulnerability is higher. However, this effect is lower if we interact the vulnerability of a company to a specific hazard with the tendency of investors to invest more in their home country. Where our findings also account for the countries' insurance protection gap.

We face two main challenges in implementing the previously explained empirical setting of our event study: i) limited access to information on firms' physical assets and difficulty translating economic losses into financial losses and price shocks (Bressan et al., 2022); ii) limited sample size of time series. To overcome the first challenge, we use the E-PRTR register

[5] Amadeus-Orbis is a product on companies' owners Bureau van Dijk a Moody's analitics company

[6] The case studies we implement were selected by the European Insurance and Occupational Pensions Authority (EIOPA), based on their relevance in terms of damages except for the case study on floods, which is based on the floods in May 2013 which is outside the timeframe of our analysis. For floods, we analyse the July 2021 summer floods as they caused around € 50 billion of economic damage as reported in the 8th EAP

to identify the location of production facilities. We then ensure that we only keep stocks with a price above € 5 during the estimation period and that have at least 10% free float, a common practice in other studies (Barnett, 2023). To overcome the second challenge, we estimate the counterfactual during the event window using a fixed 90-day estimation window of daily returns free of weather related disaster event for every company and every event. By doing so we are close to the 120 days estimation period implemented by Kruttli et al. (2023). Additionally, although we only keep those companies without weather related disasters in the estimation period, we gain companies for a wider cross section on which the measures of abnormal returns are based. As such we balance out the loss of information in the time series by gaining it in the cross section.

Our work is also relevant to European institutions and finance practitioners. As for the institutions, we test the suitability of available datasets for climate finance purposes. For instance, we believe that the E-PRTR needs more information on the workforce of the facilities, as well as their financial value and current level of adaptation measures. This would ensure a clear damage estimate and more in-depth financial analysis. In terms of the weather related disasters provided by Copernicus, they show a good and precise geographic coverage, however storms with lower wind intensity for 2018 and 2019 are missing and no data for tropical mediterranean storms is provided. For practitioners, we show the usefulness of developing alternative data measurements independent of ESG rating providers that can be used also for research in the biodiversity context.

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

I Informational barriers, disaster uncertainty and stocks

International asset allocation is less efficient than in theory due to frictions that make access to information more costly for investors (Pellegrino et al., 2022). In a recent model developed by Pellegrino et al. (2022), the representative investor z is endowed with a prior distribution of information to form expectations based on free accessible information and additional costly signals. Costly signals are modelled to negatively impact the utility function of a representative investor z. The authors define the utility function of agent z born in country j at time t as

$$\mathcal{U}(z) = (1-\lambda_j) log\, c_t(z) + \lambda_j \mathbb{E}_t[log\, c_{t+1} - \mathcal{I}(z)] + \mathcal{V}(q_{j.t}, q_{j.t+1}). \tag{1}$$

In the utility function, the patience factor λ_j that affects agent's z consumption $log\, c_{t;t+1}$ varies by country. Additionally, the utility of agent z is negatively affected by the information acquisition cost of agent $\mathcal{I}(z)$. Here, $\mathcal{I}(z)$ is defined as follows

$$\mathcal{I}(z) = \frac{1-\rho}{\rho}[H(G_{jt}) - \mathbb{E}_t H(F_t(z))] \tag{2}$$

Where G_{jt} is the distribution of returns based solely on freely accessible information and $F_t(z)$ is based on additional costly signals. The information parameter $\rho \in (0,1)$ captures the efficiency of the information processing technology: a higher value of ρ is associated with a lower cost of the information processing. This is higher if information processing technology ρ is less efficient and if the difference between the prior and posterior information distributions is lower. Finally, $\mathcal{V}(q_{j.t}, q_{j.t+1})$ is the added utility of a public good provided by country j. Intuition is that if the difference in expectations between free and costly information is low, then investors will experience less utility loss. This aspect is important to understand that if information access abroad is costly, then investors will invest in their home country where access is more likely to be for free and the difference in expectations is lower.

Since investors experience a loss of utility in acquiring costly information, their asset allocation is biased by this assumption. In Pellegrino et al. (2022) investors' share of home assets depends on the information processing technology ρ and a precision parameter ψ_{ij}. In the model, the investors of the country j' have an information advantage for certain assets: that is, the investors of j have an information advantage for i assets if the precision parameter ψ_{ij} is high. Therefore, they account for uncertainties to play a role in the decision of investors from the country j'. The country-level portfolio shares of country j that are invested in assets of country i are defined as

$$\pi_{ij} = \frac{R_i^{(\frac{\rho}{1-\rho})}\psi_{ij}}{\sum_i^n R_i^{(\frac{\rho}{1-\rho})}\psi_{ij}}. \tag{3}$$

The intuition here is that ρ increases the elasticity of the shares with respect to the net returns R_i. In other words, the easier it is to acquire information, the more elastic the shares are to net returns, and the capital is only allocated there where investors achieve the highest net returns. Translating Equation (3) into a model with barriers means defining the precision parameter ψ_{ij} to be inversely related to the informational distance. In other words, the higher the distance, the lower ψ_{ij}.

This model, together with a strain of empirical literature, explains the preference of investors to invest in their home countries or "*closer*" to them. Pellegrino et al. (2022) show that "*closer*" is related to the cultural, geographical, and linguistic proximity between countries. From an investor's perspective, a higher difference in opinions among investors is a source of uncertainty, which even in small amounts can lead to significant differences in the long-term beliefs of agents (Acemoglu et al., 2016). In Europe, investors reserve a different treatment for equally risky investments, in terms of climate risk, depending on whether they are located at home or abroad (Boermans and Galema, 2023).

Asset allocation is not only driven by informational barriers, but also by uncertainty related to weather-related disasters that impact investors decisions. Kruttli et al. (2023) developed a model to explain how the uncertainty related to extreme weather events impacts investors' and firms' returns in segmented markets. In a standard CAPM world, idiosyncratic and local events, such as weather-related disasters (e.g., Hurricanes (Strobl, 2011)) are diversified and have no impact on the discount rate of the representative investor. However, MERTON (1987) showed that in segmented markets there is underdiversification, and even shocks to idiosyncratic volatility have an impact on expected returns. MERTON (1987) argue that investors only invest in securities they know about, leading to segmented markets.

Consequently, assuming that investors asset allocation choices are driven by the informational barriers presented by Pellegrino et al. (2022), then Kruttli et al. (2023) contribution is relevant. Kruttli et al. (2023) show that uncertainty related to weather-related disasters impacts asset prices in segmented markets. Kruttli et al. (2023) extend the model by MERTON (1987) and includes the impact of weather-related disasters on the value and volatility of companies. Kruttli et al. (2023) hypothesise that two uncertainties impact cash flows: the physical probability of an event hitting a company and the uncertainty on the real entity of the damage once the company is hit. The variance of firm i in segmented markets under Kruttli et al. (2023) is defined as

$$Var(\tilde{R}_i) = b_i^2 + \sigma_i^2 + \sigma_{g,i}^2\phi + \mu_{g,i}^2\phi(1-\phi). \tag{4}$$

In Equation (4), b_i^2 is the variance driven by the market factor, σ_i^2 is the idiosyncratic variance of the firm, $\sigma_{g,i}^2\phi$, is the uncertainty of the expected impact conditional on the company being hit by the disaster and $\mu_{g,i}^2\phi(1-\phi)$ the amount of variance driven by the probability of the company being impacted by the disasters. The last two components of Equation (4) depend on ϕ, which is the probability that a firm will be hit by a weather-related disaster. While $\mu_{g,i}^2\phi(1-\phi)$ is only positive if a company is not hit by an event as long as the event last, $\sigma_{g,i}^2\phi$ is positive also after the event hit the company. Where, since ϕ is a probability when it is 0 there is no probability that an event will hit the company and when it is 1 then the event already hit the company. Depending on the value of ϕ the value of Equation (4) will change.

Clearly, if the variance of the firm's returns is impacted by the uncertainty related to the disaster, so is the firm's value and share price. Kruttli et al. (2023) link investors knowledge about firm i with the uncertainty of weather-related disasters and the value of the firm. The authors define firm value as

$$V_i = \frac{I_i}{R^f}\left[\mu_i + \mu_{\eta,i}\phi - a_i b\delta - \frac{\delta I_i(s_i^2 + \sigma_{\eta,i}^2\phi + \mu_{\eta,i}^2\phi(1-\phi))}{q_i M}\right] \tag{5}$$

In Equation (5), $\frac{I_i}{R^f}$ is the definition of discounted investments that if multiplied by the other elements of the equation leads to different components of the cash flow. While $\mu_i, a_i b\delta$ are factors that drive cash flows but are not related to the uncertainty of the disaster, weather-related disasters affect Equation (5) in two ways. First through $\mu^2_{\eta,i}$ which is the expected impact of the disaster on the firm's cash flows, and trough $\sigma^2_{\eta,i}\phi + \mu^2_{\eta,i}\phi(1-\phi))$, which is the composite effect of the weather-related disaster on the cash flow variance of the firm. Uncertainty related to disasters negatively impacts firm value if it exceeds positive impacts and is exacerbated if $q_i M$ or the share of wealth of investors who know about firm i is low. In other words, for a higher level of market segmentation, prices should become more negative.

Kruttli et al. (2023) show that many firms experience negative cumulative abnormal returns in the short term. In the specific, more than 50% of the impacted firms experience negative cumulative abnormal returns (CAR) even until 120 days after hurricane inception compared to their non-impacted peers. Nevertheless, a weather related disaster is likely to lead to a large cross-sectional dispersion in CAR of hit firms with either negative or positive effects.

II Hypotheses

Based on the theory introduced in Section (I) we know that investors have informational barriers in their investment behaviour and that these barriers are likely to impact investors' pricing behaviour during the occurrence of weather related disasters. Consequently, we formulate several hypotheses based on Section (I).

From Equation (5) we know that CAR can become negative under market segmentation and uncertainty of weather-related disasters. Consequently, weather-related disasters that can be better predicted, such as winter windstorms, should suffer more from the negative uncertainty from Equation (5) compared to floods and wildfires. Therefore, our first hypothesis is

H_1: *Weather-related disaster events with a higher predictability have a more negative impact on the cumulative average abnormal returns (CAAR) of the companies hit*

From Equation (5) and the subsequent paragraphs, we know that investors have a lower ψ_{ij} if informational disatance is higher and thus allocate fewer assets to shares they do not know with a higher information distance. Furthermore, from Equation (5) we know that weather-related uncertainty has a stronger negative impact on segmented markets. For this reason, whenever a facility is located in a different country than headquarters of the public listed company linked to the facility then investors' knowledge will be less precise, thus leading to stronger negative abnormal returns compared to the benchmark. Intuitively, companies do not disclose their exposure to weather-related disasters, and it might be more costly for investors to know facilities exposure to weather-related disasters if they are in a different country than the one of their headquarters. We define our second hypothesis as

H_2: *When a facility is located in the same country as the headquarters, investors have an* *informational advantage compared to when it is located abroad. Consequently, investors will react more negatively to a negative signal depending on whether the facility is located in the same country of the headquarters or not.*

Additionally, in Section (I) we learnt that home investors have an informational advantage in terms of informational distance; as such, we expect companies for which institutional investors have on average a higher preference for home investments to experience a lower surprise from weather-related disasters. This is so for two reasons; first, they will have done a thorough due diligence, thus increasing information precision, and will be less impacted by information distance from their home companies. Second, institutional investors will experience less information asymmetry, and thus uncertainty after the event occurrence due to their stronger ties with home companies. From this follows our next hypothesis:

H_3: *The higher the degree of home equity preference from the average institutional investor in a company, the lower the negative CAR.*

Finally, we want to investigate whether a shock in a risky region leads to a stronger investor's surprise compared to a less risky one. In other words, investors update their beliefs stronger in a riskier region because for most of them the realisation of physical risks will be a surprise since the information costs are too high to purchase them. Nevertheless, whenever the investors' base has a higher preference for home investments, the surprise is lower, as this information is easier to access for investors from the home country. Therefore, our last hypothesis is

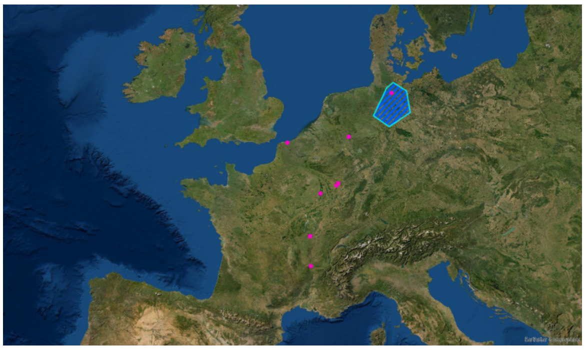
H_4: *Riskier non-insured companies should experience a more negative CAR, but whenever risk is interacted with investors' home equity preference then CAR should be comparably more positive.*

III The empirical setting and physical risk scores

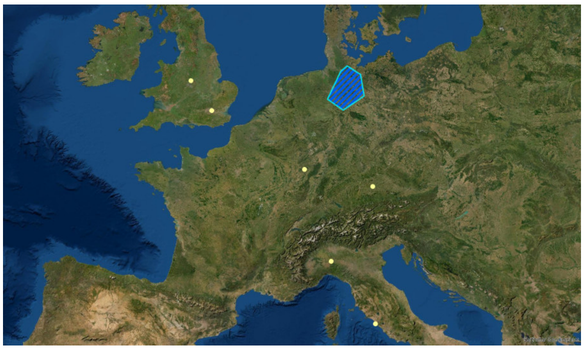
III.a The event study

To implement an event study on how extreme weather events affect investors' perceptions on the pricing of companies' shares we define the event window and the events of interests following MacKinlay (1997). Events of interest are major windstorms, floods, and wildfires that occurred in Europe since 1 January 2014 and until 31 December 2021. The time frame is set to account for increased investor attention towards climate change that led to the Paris Agreement on 12 December 2015. Following Nagar and Schoenfeld (2021) the event window to investigate price movements of companies' stocks begins five days preceding landfall for windstorms, two days before the occurrence for floods, and one day for wildfires. The event window ends twenty-two days after the beginning of the event to allow all market participants to adjust their positions.

We define several criteria for the allocation of firms to the sample. For our study, we will include only publicly listed companies that owned a production facility in an impacted area at the time a major climate hazard occurred. Figure (15) provides an example of our flood selection criteria; similar applies for windstorms and wildfires. Company Y, shown in Figure (1a), has an industrial site located in the area affected by the flood in July 2017 and is included in our study. Company X, in Figure (1b), does not have an industrial site in the affected area and is excluded from our sample.



(a) Company Y is included



(b) Company X is not included

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

We compute expected returns, with the Market model and all well-known and widely used factor models by Fama, French, and Carhart (Fama and French, 1993; Carhart, 1997; Fama and French, 2015, 2018). We opt for the market model as this is commonly used to predict expected returns. Additionally, a large body of literature suggests that different factors, which we draw from the Kenneth French Data library, are important in explaining the returns on equity portfolios. In our event study, we include those factor models that are most established in the literature and investigate whether they all point to the same results.

We implement several measures to avoid bias in the estimates due to the occurrence of several events. First, we set the estimation window for an event to stop before the first occurrence of each event. Second, in the event study, we only keep those companies for which we have an estimation window without events of the same nature. This ensures that we isolate the idiosyncratic damage of events generated by the specific occurrence.

In our analysis, we balance the precision of the estimates necessary to compute the expected returns for firm i, following from a longer estimation window (e.g., longer time series for the estimates), with the one from a larger sample size (e.g., wider cross section). A typical estimation window is characterised by 120 days (e.g., Kruttli et al. (2023)). We decide to balance the need to keep as many companies as possible for each event with the desire to increase the precision of our coefficient estimates for the different expected returns models (e.g., Fama, French and Carhart). Consequently, we opt for a 90-day estimation window to estimate the coefficients for the expected returns of firm i. Although we acknowledge that a longer estimation period increases the estimation quality, we believe that the benefits from a larger cross section outweigh the losses from a lower estimates precision for each firm, thus preserving the estimate precision. In Figure (2) we summarise the relevant information on the length of the estimation and the event window.

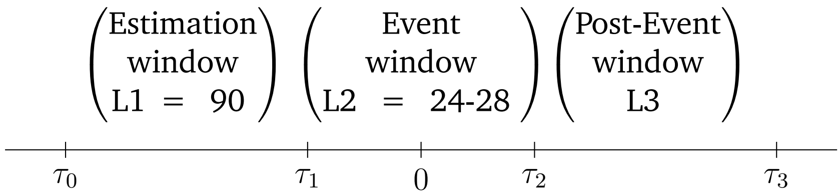


Figure 2. The windows of the event study are fixed for all events: In the figure above L_1, L_2, and L_3 are defined in days. For example, the estimation window is characterised by a period of 90 days.Where L_2 varies depending on the type of hazard (e.g. 28 for winter storms as they are highly predictable).

Then, we compute abnormal returns using all the models listed above for expected returns. We define abnormal returns as follows.

$$\begin{aligned} \underbrace{AR_{ie}}_{(L_2 \times 1)} &= R_{ie} - E[R_{ie}|X_{ie}] \textit{ where} \\ \underbrace{E[R_{ie}|X_{ie}]}_{L_2 \times 1} &= X'_{ie}\beta_{ie} \textit{ and} \\ \underbrace{\hat{\beta}_{ie}}_{j \times 1} &= (X'_{ie}X_{ie})^{-1}X_{ie}R_{ie} \end{aligned} \tag{6}$$

In Equation (6) R_{ie} are actual returns and X_{ie} are different factors depending on the estimation model for $\hat{\beta}_{ie}$ for firm i and event e. In our study, we compute cumulative average abnormal returns generated by extreme weather events over many events and companies. Consequently, we aggregate Equation (6) first over time and then over companies as follows.

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

$$CAAR_t = \frac{1}{N}\sum_{i=1}^{N} CAR_{i,t}. \tag{8}$$

In Equation (8) N is the number of companies in every event and t is a specific day of the event window that goes from τ_1 to τ_2. We compute CAAR as the cross-sectional average over firms' CAR. To ensure the robustness of our results, we compute the standardised cross-sectional variance from Boehmer et al. (1991) that is robust to any variance induced by the event (Boehmer et al., 1991; Kolari and Pynnönen, 2010). For completeness, we calculate the Corrado rank test for the small sample size of windstorms (Corrado, 1989). This is so as abnormal returns might turn to significant due to a higher event-induced variance, thus leading a normal parametric test to higher rejection rates than usual. With this decision we ensure that we are not rejecting the null hypothesis ($H_0 : E(CAR) = 0$), although this is true, due to the relatively low power of this test statistic. More information on the technical implementation of (Boehmer et al., 1991) is included in Appendix (A).

III.b Physical risk scores

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

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

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

$$p_n = \frac{P_{T_n} - 1}{\prod_{i=T_1}^{T_n} (1 - p_i)} + 1 \tag{9}$$

In Equation (9) P_{T_n} is the number of times a stochastic process exceeds some critical value, in this case related to the return period, per unit of time (e.g., the probability that a wind intensity goes above 100 km/h in the next 10 years). We then define the return period as T_n, p_n as the probability of occurrence for the same return period, and p_i as the probability of occurrence for a single event. In practice, we would compute the probability of occurrence for different periods as in the following examples. Assume the following return periods T_{100}, T_{50}, T_{10}. The probability of occurrence for the longest return period (e.g.,T_{100}) is equal to the probability of exceedance. From that we can then calculate all other individual probabilities associated with the events.

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

In Equation (10) $j = 1$ and i change depending on the return period. For example, $p_{100,1}$ is probability of occurrence with return periods of 100 years for one year. Consequently, since events are assumed to be independent, we express EAL for all events in one year as

$$EAL = \sum_{i=T_1}^{T_n} (p_i L_i). \tag{11}$$

In Equation (11), L_i is the percentage loss for all physical assets the company has for a given hazard that occurs with a given intensity for a given location accounting for the use of the land and the distribution of the buildings in that area.

We compute EAL at the facility level and aggregate them over the facilities by company. To compute EAL or risk scores by companies, we aggregate EAL from a facility level to a company level. In a second step, as suggested in the methodology of the Statistics Committee of the ESCB (2023) we create five buckets based on the EAL 20% quantiles. Where the lowest 20% EAL gets a value of 0 and the highest a value of 4. We compute risk scores only for windstorms and floods, as only for those a methodology is available.

III.c Measuring the preference for home stocks

We calculate the ownership of home equity at the company level by aggregating the investments of all institutional owners (IO) in a company by country. For example, $IO1$ invests in company A and is from country A, while $IO2$ and $IO3$ invest in companies A, C and are from countries A, B, respectively. Then the preference for home equity of all IO investing in company A is given by the sum of the investments of $IO1$ and $IO2$ in A. This measure is the home bias measure of Coeurdacier and Rey (2013) applied at the company level instead of the country level. Consequently, we collect all the IO investments in the companies of our sample and assign them to home or abroad depending on their country of residence for every company. Here IO are more informed investors, in general, and we believe that our result will provide a conservative lower bound estimate. We define home equity home bias (EHB) on the company level as follows

$$EHB_{i,t} = 1 - \left(\frac{\textit{Share of foreign institutional ownership in company } i \textit{ at time } t}{\textit{Share institutional ownership in company } i \textit{ at time } t} \right). \tag{12}$$

We use the EHB measure as a proxy for the general home preference of investors in company i. We replicate Graph (1) from Coeurdacier and Rey (2013), where the authors plot the degree of home bias by shares of domestic holdings in total holdings for selected countries with our data. We find very similar distributions by country, thus meaning that our data set does not deviate from previous literature in the field.

IV Sample and data sources

In our analysis, we focus on the weather related disasters that are mostly relevant for Europe in terms of damages: floods, wildfires, and winterstorms (EIOPA, 2022). There is also an increasing trend in terms of damage, as highlighted in the 8th EAP report from the EEA. In Figure (3) we show that also in the timeframe analysed there is an upward trend in the average historical frequency of climate hazards.

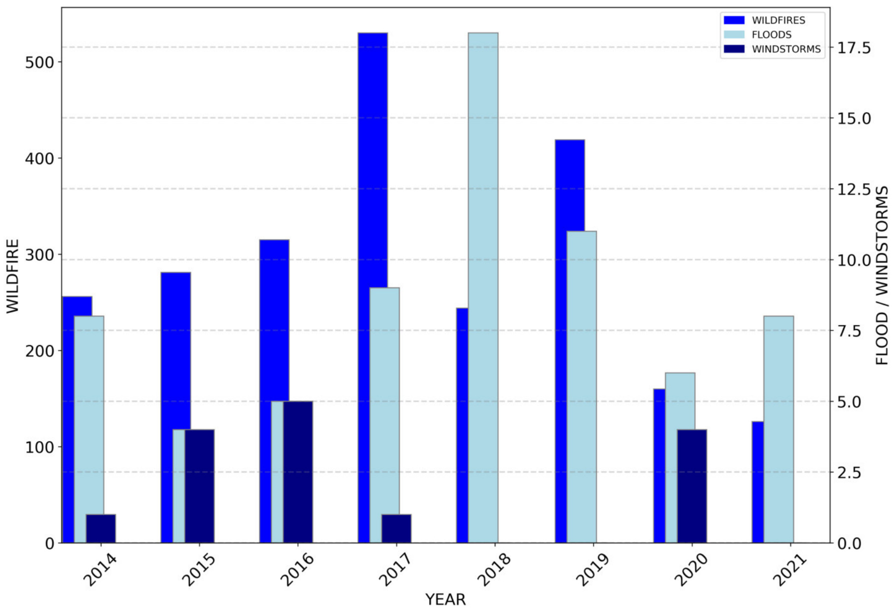


Figure 3. Hazards frequency by year and type: In Figure (3), we show the frequency of major climate hazard in Europe by year. On the left y-axis wildfires and on the right floods and winter windstorms.

We analyse how investors of publicly listed entities in Europe react to the impact of different hazard types, merging several sources. First, the location of facilities and their ownership structure is obtained by merging the E-PRTR with Amadeus ownership data from Bureau van Dijk.[7] Second, we match the resulting dataset with the daily historical returns and stock

[7] In this version of the paper we still assume that ownership structures in a company do not change for 4 years. Thus, we take two snapshots of Amadeus ownership (2018-2022) and assume that they have the same ownership

ownership over time. Third, we use facilities' locations, hazards timing, and location to identify when and where companies are impacted by hazards. More information on single data sets and matching methodologies between sources are in Appendix (B,D).

In general, we identify 1,748 facilities owned by around 600 unique publicly listed companies that have been impacted by weather-related disasters (e.g., floods, wildfires, winter wind storms). This number is in line with similar work on physical risks using facility data outside the US (Bressan et al., 2022). The sample results from several assumptions on hazard and stocks. First, in the event window, when hazards recur several times, we only consider the first occurrence for the same company. In the event window, we believe that the first event is more likely to bring investors to update their risk preferences. In the estimation window companies are only included if there is not the same weather-related disaster biasing the estimation window. Second, this sample is cleaned from penny stocks (e.g. price less than € 5 before the event) in the estimation period of the event, from some financial companies (not those in the insurance sector) and those that have less than 10% free float. These measures account for the liquidity and microstructure effects of stocks and are standard in the literature (Barnett et al., 2021). Finally, facilities are considered to be owned by a publicly listed company if between the facility owner and the publicly listed company there is a 50 % ownership chain.

The companies that populate the sample are financially sound, materially relevant, and distributed throughout Europe. Companies are historically overvalued because market evaluations exceed book values with a median ratio of around 55%. They have a ratio of tangible assets to total assets of 86%. Furthermore, the median debt-to-asset ratio is 26% and the short debt-to-debt ratio is around 20%. The median market capitalisation of companies in our sample is historically € 3.65 billion, which is almost half of the current median market capitalisation of the EUROSTOXX 600 index. In Table (III) in Appendix (D) we see that France, Germany, Italy, the United Kingdom, and Spain are relevant countries for the percentage of impacted facilities that are publicly listed. In general, of the 4,138 facilities that we could link to a publicly listed provider around 42% are affected at least once by one type of weather-related disaster. Finally, the sample is materially relevant in terms of economic exposure to physical risk, including sectors such as agriculture, manufacturing, utilities, water, and mining that are highly exposed to weather-related disasters, as shown by Dunz et al. (2021). The manufacturing sector represents around 20% of all facilities that are owned by public entities and are affected by hazards. In Table (IV) in Appendix (D) we provide additional details.

We identified 181 unique publicly listed companies whose facilities are affected by 16 windstorms. Windstorms are heterogeneously distributed throughout Northern Europe. The average historical maximum 3-second 10m wind gust over time and events is 34 km/h. Where a wind speed of above 30 km/h is considered to be damaging to most European buildings

backward until 4 years before.

(Prahl et al., 2016) . The event date considered is that of landfall as suggested in (Lanfear et al., 2019). Many highly capitalised companies are included in the sample, such as Total Energies, Novartis, and General Electric.

(a) Winter windstorms (2014-2021)

(b) Wildfires (2014-2021)

(c) Floods (2014-2021)

Figure 4. Companies impacted by different hazards from 2014 to 2021: In Sub-Figure (4a), we show names of all companies impacted by winter windstorms. The bigger the font size the higher the market capitalization of the company. In Sub-Figure (4b), we show those of companies impacted by wildfires in Europe from 2014 to 2021. In Sub-Figure (4c), we show companies impacted by floods in Europe the same timeframe

Additionally, we identify 136 unique public listed companies that have been impacted by 2,332 wildfires since 2014. Active fires provide us with the exact timing, type, and location of an active fire, while burnt areas give us the extent of damage caused by the event. The Sub-Figure (4b) provides the sample of company names by market capitalisation. impacted by wildfires in Europe since 2014. Here, we find some highly capitalised companies in the sample such as Unilever, Exxon Mobil and Nestle.

For floods, we find that 438 unique listed companies are affected by 68 flood events between 2014 and 2021. Most of the events take place in Central and Southern Europe. In the specific 10 in Spain, 8 in Italy, 10 in France, 7 in Greece, and 5 in the United Kingdom, among others. Sub-Figure (4c) shows the names of companies impacted by floods ranked by market capitalisation. In the Sub-Figure we find companies such as Johnson & Johnson, Nestle, Bayer AG, Total Energies and Astrazeneca.

V CAAR and EHB

V.a Case studies on major historical events

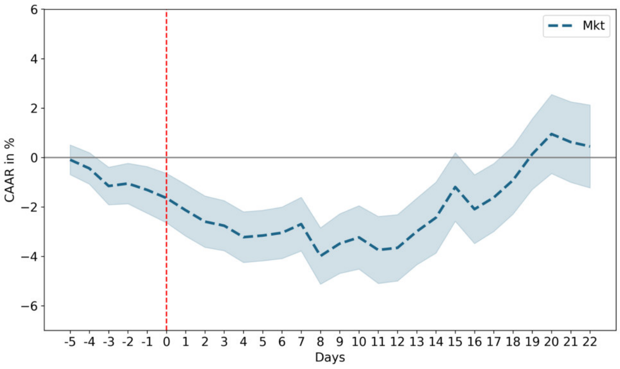
Our analysis lacks company-reported financial damages and therefore we first investigate our methodology on three case studies that were reported to cause serious damage in Europe. These events are of particular significance not only due to their potential economic consequences, but also due to their prominence in recent reports, including those from EIOPA and the EEA. Our inquiry involves scrutinising CAAR that encompasses these events, in order to uncover deviations from expected market trends. We use three case studies as essential building blocks, laying the groundwork for a more comprehensive analysis that encompasses all weather-related disasters. This broader examination enables us to gain a panoramic understanding of market dynamics in the face of adverse conditions. In Appendix (E.b) we present CAAR with an industry breakdown of this analysis.

To avoid unnecessary repetitions, we define the terms "$Home$" and "$Abroad$" for the following sections. "$Home$" is when the facility impacted by an weather-related disaster is located in the same country as the headquarters of the publicly listed company linked to it through ownership. "$Abroad$" is the definition used to characterise the affected facility located in a different country compared to the headquarters of the publicly listed company linked to the affected facility.

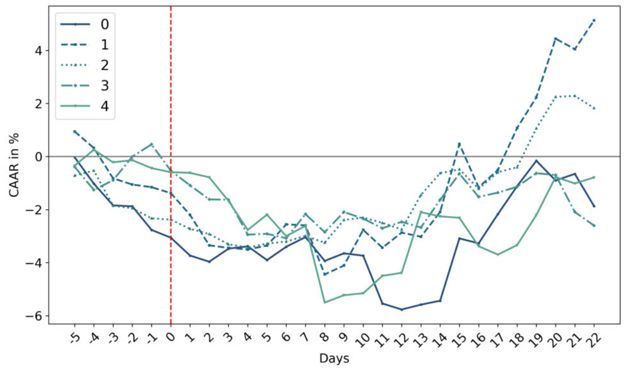
V.a.1 Windstorm Ciara 2020

We first analyse winter windstorm Ciara that impacted Northern Europe from 7 to 11 February 2020. A distinct pattern emerges, revealing statistically significant and negative CAAR centered precisely around the event date (see Sub-Figure (5a)). This indicates a rapid and unanimous market response to winter storms, underscoring investors' ability to swiftly integrate anticipated economic consequences into stock prices. Significantly, our study introduces an innovative dimension by investigating the influence of a company's facilities' geographic location on the event's impact. Our findings reveal that companies with "$Home$" impacted facilities exhibit an attenuated negative impact of winter storms on stock returns compared to those with facilities "$Abroad$" (see Sub-Figures (5c) and (5e)). This intriguing divergence underscores the need to consider firm-specific characteristics in market reactions.

We then analyse CAAR by risk and facility location. We assign companies to the relative windstorm risk bucket based on the EAL with risk score 4 being the highest risk possible. When considering all impacted companies, we see that lower risk broadly leads to higher surprise (See Sub-Figure (5b)). By differentiating based on "$Home$" or "$Abroad$" we find different reactions. If the facility is located "$Abroad$", investors are similarly surprised by all risk levels, hinting at a possible mispricing for the specific risk (See Sub-Figure (5f)). On the other hand, if the facility is located "$Home$", then greater knowledge on higher risk buckets leads to a lower overall surprise (See Sub-Figure (5d)).



(a) All



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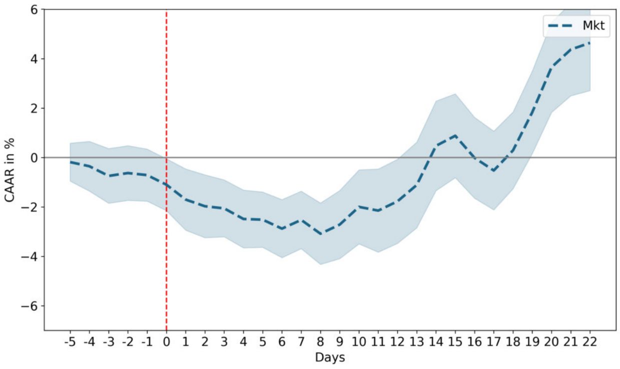
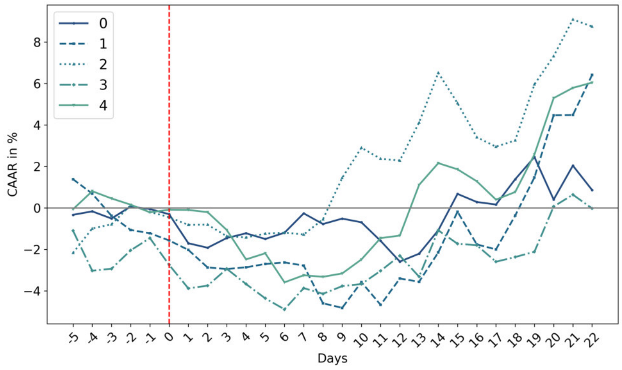
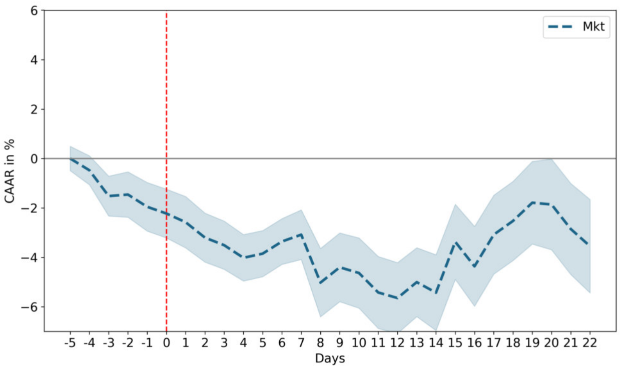


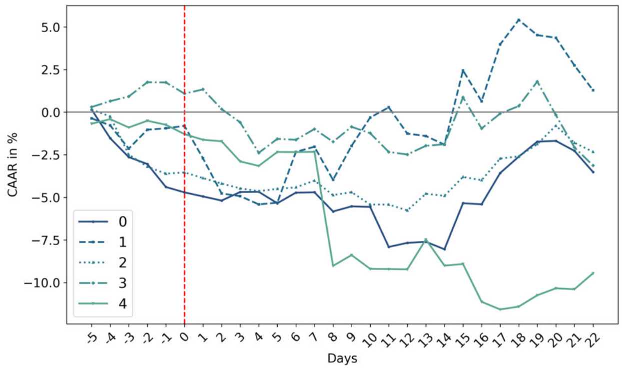
(c) “*Home*"



(d) “*Home*"



(e) “*Abroad*"



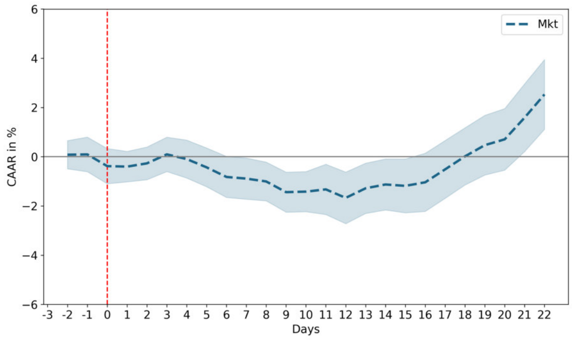
(f) “*Abroad*"

Figure 5. CAAR for Windstorm Ciara February 2020: In Sub-Figure (5a), we depict CAAR for companies impacted by winter windstorm Ciara which formed on 3 February 2020 and dissipated on 16 February 2020 independent of the location of the facility compared to its headquarters, in Sub-Figure (5c) we show CAAR of those companies whose facilities are “*Home*" and and in Sub-Figure (5e) for those companies whose facilities are located “*Abroad*". The Y-axis of each figure represents CAAR in %, and the X-axis days from the event, where positive values are after event beginning and negative before. Finally, in Sub-Figures (5b),(5d) and (5f) we disentangle the CAAR by risk buckets, where risk buckets are created using the quintiles of the the EAL distribution.

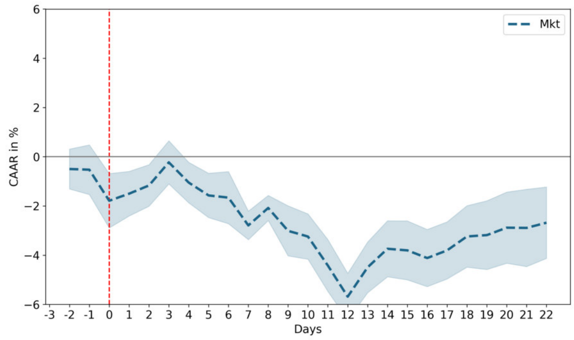
V.a.1 Wildfires summer season 2017

Shifting our focus to the wildfires in Portugal and Spain from June to October 2017 we uncover a negative trend in CAAR following wildfire events. However, this negative trend is significantly different from zero only 12 days after the start of the wildfire (see Figure 6).

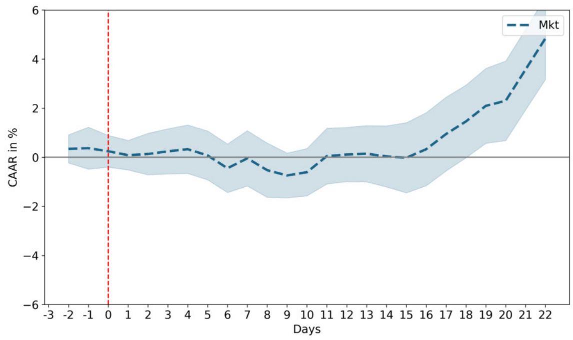
While discernible market responses are evident, it becomes apparent that additional factors may mitigate investors' reactions to wildfire events. When looking for facilities located "*Home*", we find that the negative trend is considerably stronger at the event date and recovers around 22 days after the event (see Sub-Figure (6b)). On the other hand, when the facility is "*Abroad*" we do not find evidence of negative CAAR at event date (see Sub-Figure 6c). Overall, from the differences in Sub-Figures (6b) and (6c) we see that there is a discrepancy between the market reaction depending on whether the facility is "*Home*" or "*Abroad*". These results should be taken with caution as the sample size is of 9 companies.



(a) All



(b) "*Home*"



(c) "*Abroad*"

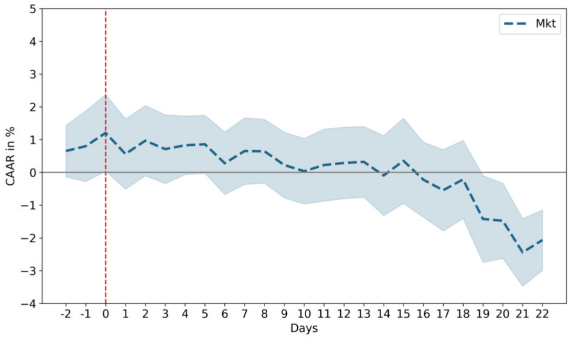
Figure 6. CAAR for the Wildfire Season in Portugal and Spain 2017: In Sub-Figure (6a), we depict CAAR for companies impacted by Wildfire season in Portugal and Spain from August to October 2017 independent of the location of the facility compared to its headquarters, in Sub-Figure (6b) we show CAAR of those companies whose facilities impacted were in the same country and in Sub-Figure (6c) for those companies whose facilities are located abroad. The Y-axis of each figure represents CAAR in %, and the X-axis days from the event, where positive values are after event beginning and negative before.

V.a.1 Northern European Summer floods 2021

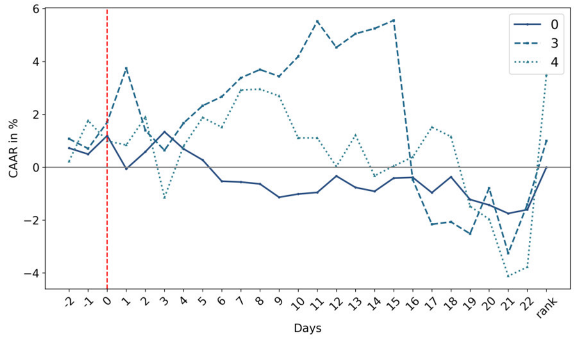
Lastly, our case study analysis looks at the summer floods in July 2021 that strongly impacted Belgium, Germany, and the Netherlands. Here, CAAR become negative over time and only at month end significantly different from zero (see Sub-Figures (7a,7c,7e)). Moreover, we identify a compelling disparity in market behaviour based on the geographic location of the affected facilities of a company. Specifically, for companies with affected facilities at "*Home*", the initial response suggests market optimism on the companies' ability to recover (see Sub-Figure (7c)). This phenomenon is absent when the affected facilities are located "*Abroad*".

However, CAAR are negative and significantly different from zero around 10 days after the event for the 4 and 5 factor models as shown in Table (XVIII) in the Appendix (E.c).

When comparing investors' surprise related to the companies' exposure to flood risk, we find that home investors are less surprised than foreign investors. In general, floods do not trigger a strong surprise relative to risk exposure (7b). However, when comparing market reactions for "$Home$" and "$Abroad$" we find that for facilities "$Abroad$" investors are less protected than when the facility is at "$Home$" (See Sub-Figures (7d) and (7f)). These results show that collecting knowledge on exposure to flood risks is more cumbersome "$Abroad$" than "$Home$".



(a) All



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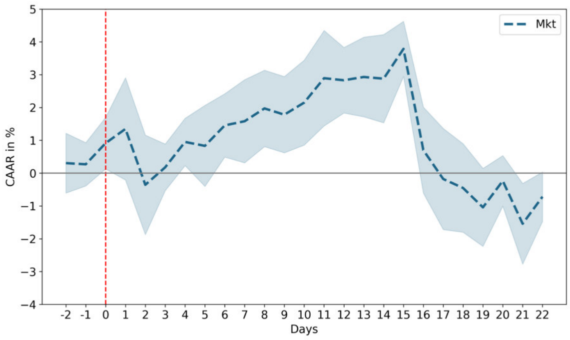
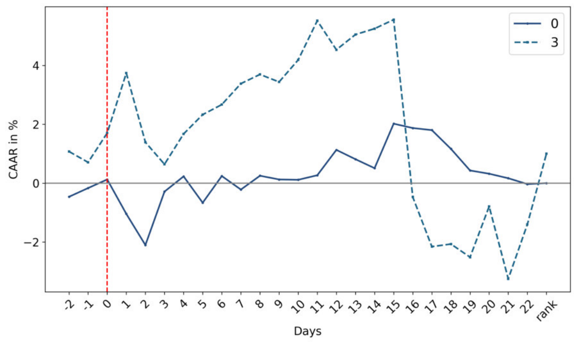
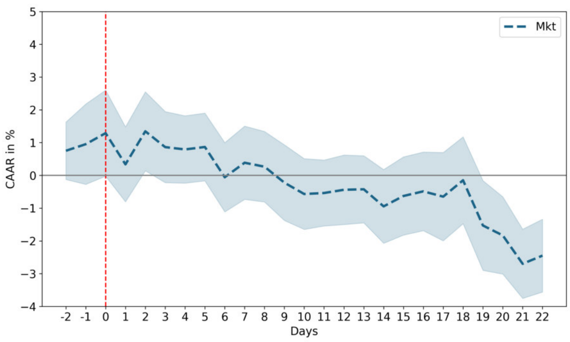


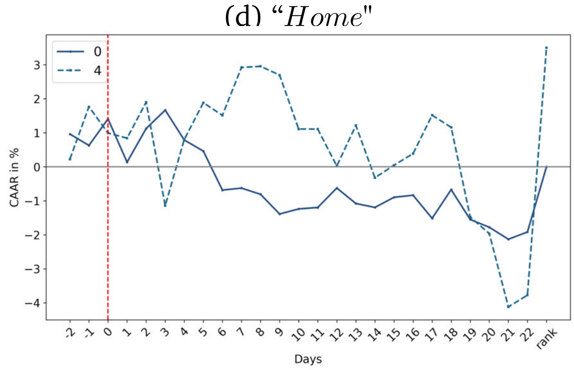
(c) "$Home$"



(d) "$Home$"



(e) "$Abroad$"

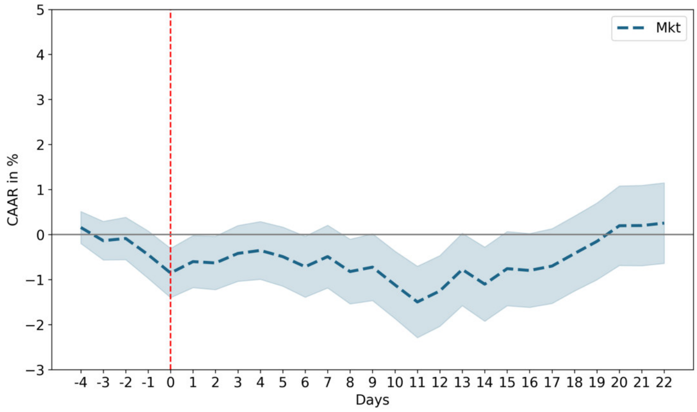


(f) "$Abroad$"

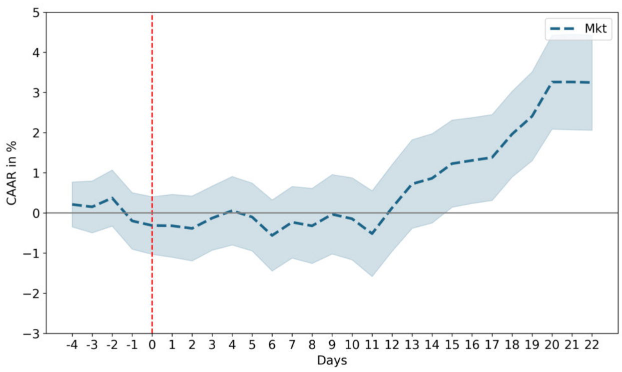
Figure 7. CAAR for the summer floods in Central Europe July 2021: In Sub-Figure (7a), we depict CAAR for companies impacted by the summer floods in Germany, Belgium and the Netherlands from 13 to 15 July 2021 independent of the location of the facility compared to its headquarters, in Sub-Figure (7c) we show CAAR of those companies whose facilities impacted were in the same country and in Sub-Figure (7e) for those companies whose facilities are located abroad. The Y-axis of each figure represents CAAR in %, and the X-axis days from the event, where positive values are after the beginning of the event and negative before. Finally, in Sub-Figures (7b),(7d) and (7f) we disentangle the CAAR by risk buckets, where risk buckets are created using the quintiles of the EAL distribution.

V.b Extending the analysis to the entire hazards' sample

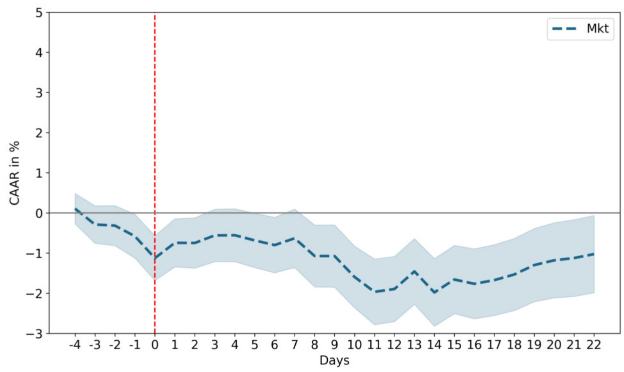
Building on the insights obtained from our individual case studies, we extend our analysis to encompass the entire spectrum of weather-related disasters. The case studies on winter storms, wildfires, and floods showcased the effectiveness of our methodology in detecting significant market adjustments in response to these adverse events. With these foundations laid, we move on to a comprehensive analysis of windstorms for which the methodology has proven to be the most effective. As for the other weather-related disasters, since the results do not differ significantly from the case studies, we provide this analysis in Appendix (E.a) for the interested reader.



(a) All



(b) "$Home$"



(c) "$Abroad$"

Figure 8. CAAR for all Windstorms: In Sub-Figure (8a) we depict CAAR for companies impacted by winter windstorms independent of the location of the facility compared to the headquarters. In Sub-Figure (8b) we depict CAAR for companies impacted by winter windstorms whose impacted facilities are located "$Home$". Finally, in Sub-Figure (8c) we depict CAAR for companies impacted by winter windstorms whose impacted facilities are located "$Abroad$".The Y-axis of each figure represents CAAR in %, and the X-axis days from the event, where positive values are after event beginning and negative before.

As observed in the winter wind storms case study, a distinct and statistically significant pattern emerges in the CAAR centered around the event date (see Sub-Figure (8a)). This reaffirms the swift and unified investors' reaction to winter storms at event date with a negative CAAR of around 1% over all investor models (See Table (XII) in Appendix (E.c)). For companies whose impacted facilities are at "$Home$" there is no evidence of a negative trend at the event date (See Sub-Figure (8b)). On the other hand, for those companies, whose facilities are located "$Abroad$" we see that CAAR reach around -1.2% at the event date and -2% in the longer period. While in Sub-Figure (8b) we see a reversal of the downward trend after 22 trading days, the same does not hold for Sub-Figure (8c) where CAAR reach -1.5% in the longer run. These results show the effectivness of our methodology to detect negative reactions on stock returns. Results are consistenly significant also using the corrado rank test (See Table(XI) in Appendix (E.c))

These results support H_1 and H_2. H_1 states that *"Weather-related disaster events with a higher predictability have a more negative impact on the cumulative average abnormal returns (CAAR) of the companies hit"*. The results on CAAR from the case studies analysis and for the whole sample show indeed that winter windstorms have a stronger negative impact on CAAR compared to wildfires and floods. Additionally,H_2 states that *"When a facility is located in the same country as the headquarters, investors have an informational advantage compared to when it is located abroad. Consequently, investors will react more negatively to a negative signal depending on whether the facility is located in the same country of the headquarters or not"*. As for H_2 we see that the results plotted for winter windstorms and floods support this hypothesis in the case studies and for winter windstorms when analysing the whole sample. As such our findings partly support H_2.

For a more comprehensive understanding of our results, we direct the interested reader to Appendix (E.c), (E.b) and (E.a). In the specific tables on CAAR for case studies are available in the Appendix (E.c). For example, in Tables (V,XIX,XX) there are tables for the Ciara windstorm. The analysis for all weather-related disasters and different measures is available, among others, in Tables (X,XII,IX) in the Appendix (E.c). A breakdown by industry is available in Appendix (E.b). Finally, additional information on wildfires and floods is available in the Appendix (E.a). By delving into the specifics of our methodology and results, these supplementary tables provide a deeper context for interpreting our broader conclusions.

V.c Analysing the impact of home equity holdings on CAR

In the previous section, we observed that there is a difference in investors' reaction to weather-related disasters depending on whether facilities are located "$Home$" or "$Abroad$". We decide to investigate this channel following the literature on home bias, as we believe that there might be informational barriers between home and foreign investors.

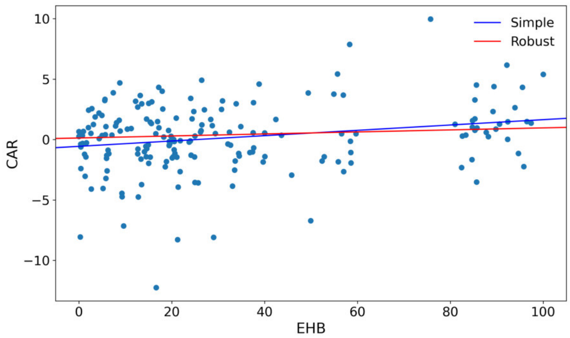
We analyse the impact of home bias on CAR in a cross-sectional setting. Since companies impacted are only included if there are at least 90 days between two events occurring, we analyse the impact of home bias on CAR using a cross-sectional approach. Our regression model is shown in Equation (13).

$$CAR_{it\Delta} = \beta_0 + \beta_1 EHB_{it} + Controls + \epsilon_{it} \tag{13}$$

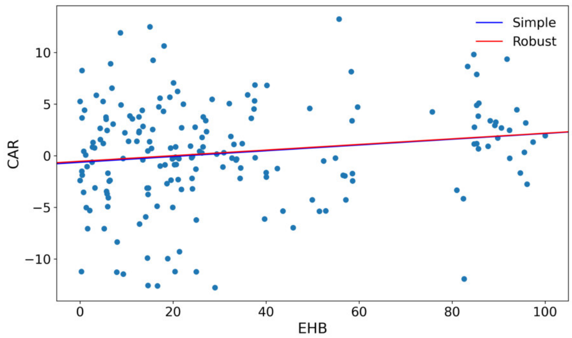
In Equation (13) $CAR_{it\Delta}$ are the CAR for company i on the date of the event t after Δ

days from the event occurrence. In a cross-section setting t is the different calender date for each company. We focus on three Δ dates: 1, 10 and 22 days after the event begins (e.g. CAR_{it10}). EHB_{it} is the home equity preference of IO investor of Company X in the quarter Y calculated using Equation (12). BM_{it},P_{it}, MC_{it},σ_{mit}, MOM_{it} and $TURN_{it}$ are, respectively, the logarithmic value of the book-to-market ratio, the log of the share price, the log of market capitalisation, the volatility of the monthly return, the momentum of the 12 month returns and the shares turnover. These variables are controls suggested in the literature (Ferreira et al., 2017b; Jia et al., 2017).

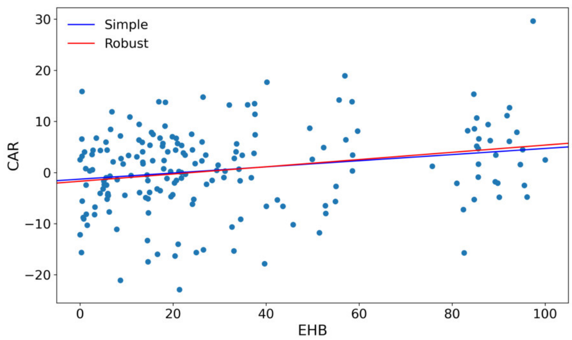
We implement three regressions for each of $CAR_{it\Delta}$ (e.g., CAR_{it1},CAR_{it10} and CAR_{it22}). The first is a simple linear regression of EHB_{it} on $CAR_{it\Delta}$, then we include the controls, and the third regression includes a robust estimator that accounts for outliers. The method we choose to account for outliers is the robust linear model that minimises the impact of outliers with a trimmered mean at 0.5% percent of observations. We visualise the impact of this method on the regression result in Figure (9) to avoid any concerns. Here is visible for winter wind storms that the regression of EHB_{it} on $CAR_{it\Delta}$ would suffer from outliers. The blue line is the simple OLS regression, and the red line is the robust estimator. The difference is minimal in both regressions.



(a) CAR_{it1}



(b) CAR_{it10}



(c) CAR_{it22}

Figure 9. Scatter Plots of EHB on $CAR_{it\Delta}$ for windstorms: In Sub-Figures (9a,9b,9c) we provide a scatterplot of $CAR_{it\Delta}$ on EHB and a line fit for the the OLS and the robust linear estimator for Winterstorms.

We also account for concerns on heteroskedasticity. We perform Breusch-Pagan tests on all regressions for the hazards and we cannot reject the null hypothesis that homoskedasticity is present. As such, we do not account for heteroskedasticity robust estimators.

In investigating the impact of EHB_{it} on $CAR_{it\Delta}$ for winter windstorms, we run nine regressions across three time intervals and three model specifications. Table (I) provides a comprehensive overview of the findings for each regression. Across all specifications, a consistent pattern emerges, revealing a positive and statistically significant association between EHB_{it} and $CAR_{it\Delta}$. Specifically, an incremental unit increase in EHB_{it} corresponds to an enhancement of $CAR_{it\Delta}$ ranging from 0.03% to 0.08%, depending on the temporal proximity to the event date. In particular, the magnitude of this relationship appears to strengthen as the temporal distance from the event widens. This consistent and discernible trend suggests that higher levels of home equity preference correspond to increased CAR, signifying a possible mechanism through which investors' affinity for domestic securities influences market adjustments in response to winter windstorms.

	Dependent variable: $CAR_{it\Delta}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
β_0	-1.96***	-1.95	-3.13***	-3.27***	-3.52	-3.60***	-0.97	-0.26	0.46
	(0.47)	(2.25)	(0.63)	(0.73)	(3.36)	(1.12)	(1.11)	(5.07)	(2.04)
EHB	0.03***	0.03***	0.03***	0.05***	0.06***	0.08***	0.02	0.05*	0.06***
	(0.01)	(0.01)	(0.00)	(0.01)	(0.02)	(0.01)	(0.02)	(0.03)	(0.01)
BM_t		0.02	-0.51***		0.43	0.61**		1.40	2.38***
		(0.51)	(0.14)		(0.76)	(0.25)		(1.14)	(0.46)
P_t		-0.42	-0.15		0.03	0.03		-0.06	-0.41
		(0.39)	(0.11)		(0.57)	(0.19)		(0.87)	(0.35)
MC_t		0.16	0.15**		0.07	-0.05		0.02	0.22
		(0.22)	(0.06)		(0.33)	(0.11)		(0.50)	(0.20)
σ_m		-0.00	0.00		0.00	0.04**		0.07	0.02
		(0.03)	(0.01)		(0.05)	(0.02)		(0.08)	(0.03)
MOM		-0.01	-0.02***		-0.02	-0.00		0.01	0.00
		(0.01)	(0.00)		(0.02)	(0.01)		(0.03)	(0.01)
TURN		-0.11	-0.53**		-1.45	-1.89***		-4.54**	-5.14***
		(0.91)	(0.25)		(1.36)	(0.45)		(2.06)	(0.83)
Observations	199	175	175	199	177	177	199	177	177
R^2	0.05	0.06		0.05	0.07		0.00	0.05	
Adjusted R^2	0.05	0.03		0.05	0.04		-0.00	0.01	

Note: *p<0.1; **p<0.05; ***p<0.01

Table I. EHB regressions for companies with facilities impacted by winter windstorms: In Table (I) we provide 9 regressions. From columns (1) to (3) we provide regressions of the independent variables on CAR_{it1}, where in column (1) the indipendent variable is EHB_{it}, in column (2) we include controls and in column (3) we include a robust estimation accounting for outliers. Similar applies for columns (4) to (6) which are a regression on CAR_{it10} and columns (7) to (9) on CAR_{it22}.

The results provided in Table (I) support H_3. H_3 states that *"The higher the degree of home equity preference from the average institutional investor in a company, the lower the negative CAR*". Clearly in Table (I) the coefficient is significant and positive across all model specifications and time intervals, thus supporting the hypothesis.

V.d Physical Risk and EHB

We test H_4, which hypothesises that *"riskier non-insured companies should experience a more negative CAR, but whenever risk is interacted with investors' home equity preference then CAR should be comparably more positive*" by extending the model from Equation (13) to include the EAL for winter windstorms and its interaction with EHB. We define the regression equation as follows.

$$CAR_{it\Delta} = \beta_0 + \beta_1 EHB_{it} + \beta_2 EAL(PR)_{it} + \beta_3 EHB_{it} * EAL(PR)_{it} + Controls + \epsilon_{it} \quad (14)$$

Where $EAL(PR)_{it}$ is the EAL in percentage for winter storms with or without the insurance protection gap provided by EIOPA. As results are similar in terms of the sign and significance of the regressors we only include the regression for windstorms including the EAL after accounting for national insurance protection to the specific weather natural disaster (Other regressions for other weather related disaster types are presented in Appendix (E.e)).

All else equal a higher vulnerability to the specific hazard leads to a more negative investors' surprise while the interaction of EHB and the EAL of windstorms reduces this impact. The results to this regressions are presented in Table (II). The impact of risk is negative whenever significant and very relevant in economic terms as it can be as high as 70 percentage points (p.p) after event date to 1044 (p.p) 22 days after event occurrence. This impact turns to be from 3 to 45 (p.p) lower when insured windstorms EAL is interacted with EHB. These results partly confirm our hypothesis that a higher EHB in the investors' base of the impacted company improves the negative investors' surprise.

VI Conclusion

Our comprehensive analysis delves into the intricate relationship between climate hazards and equity prices, offering insights that connect to the foundational questions posed in our introduction. As we traverse the landscape of winter storms, wildfires, and floods, our investigation demonstrates the influence of investor behavior on market adjustments in response to adverse events. Our empirical methodology, characterized by spatial identification, historical ownership reconstruction, and forward-looking analysis, provides a robust framework for understanding these dynamics.

Drawing from the findings summarized above, our research substantiates the theories posited in the literature, which anticipate short-term price depreciation in industries materially affected by weather-related natural disasters under informational barriers (Kruttli et al., 2023). This empirical validation echoes prior studies and contributes to our understanding of the relationship between weather-related disasters and market reactions (Kruttli et al., 2023; Huynh and Xia, 2021). Additionally, we observe how investors' perceptions vary across different disaster types, reflecting the nuanced responses of the market to specific events.

	Dependent variable: $CAR_{it\Delta}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
β_0	-1.97***	-1.94	-2.24***	-3.15***	-3.41	-3.53***	-0.86	-0.34	0.59
	(0.50)	(2.31)	(0.63)	(0.78)	(3.46)	(1.16)	(1.19)	(5.20)	(1.93)
EHB	0.03***	0.03***	0.04***	0.05***	0.06***	0.07***	0.02	0.05*	0.06***
	(0.01)	(0.01)	(0.00)	(0.02)	(0.02)	(0.01)	(0.02)	(0.03)	(0.01)
$\text{WS}_{ins_{EAL}}$	-24.23	-41.48	-70.47***	22.14	-2.68	32.35	69.56	67.17	-1044.07***
	(57.51)	(67.46)	(18.38)	(88.67)	(101.48)	(33.99)	(134.91)	(152.60)	(56.74)
$\text{WS}_{ins_{EAL}} * EHB$	0.90	1.38	2.61***	-1.86	-1.07	-2.16	-4.59	-4.60	45.11***
	(2.37)	(2.61)	(0.71)	(3.65)	(3.94)	(1.32)	(5.56)	(5.92)	(2.20)
BM_t		0.19	-0.13		0.53	0.65**		1.66	1.88***
		(0.53)	(0.15)		(0.80)	(0.27)		(1.21)	(0.45)
P_t		-0.42	-0.05		0.01	0.05		-0.06	-0.24
		(0.39)	(0.11)		(0.58)	(0.20)		(0.88)	(0.33)
MC_t		0.17	0.03		0.08	-0.06		0.04	0.04
		(0.23)	(0.06)		(0.34)	(0.11)		(0.51)	(0.19)
σ_m		-0.01	-0.01		0.00	0.04**		0.07	0.03
		(0.03)	(0.01)		(0.05)	(0.02)		(0.08)	(0.03)
MOM		-0.01	-0.02***		-0.01	-0.00		0.02	-0.01
		(0.01)	(0.00)		(0.02)	(0.01)		(0.03)	(0.01)
TURN		0.00	-0.07		-1.44	-1.86***		-4.36**	-4.87***
		(0.92)	(0.25)		(1.39)	(0.47)		(2.09)	(0.78)
N	195	172	172	195	174	174	195	174	174
R^2	0.05	0.07		0.05	0.07		0.01	0.06	

Note: *p<0.1; **p<0.05; ***p<0.01

Table II. EHB regressions for companies with facilities impacted by winter windstorms: In Table (I) we provide 9 regressions. From columns (1) to (3) we provide regressions of the independent variables on CAR_{it1}, where in column (1) the independent variable is EHB, in column (2) we include controls and in column (3) we include a robust estimation accounting for outliers. Similar applies for columns (4) to(6) which are a regression on CAR_{it10} and columns (7) to (9) on CAR_{it22}.

Furthermore, our investigation delves into the impact of IO home equity preference on market adjustments, shedding light on its significance within the context of weather related natural disasters. The consistent positive correlation between home equity preference and CAR in the cases of winter windstorms underscores the role of investor preferences in shaping market dynamics. In particular, this relationship strengthens as the temporal distance from the event widens, suggesting a gradual assimilation of information by domestic investors.

However, the picture becomes more intricate when one examines the impact of home equity preference in response to floods. Here, our findings reveal less conclusive and inconsistent results, suggesting a complex interplay of factors that influence market adjustments. The role of investor behavior in shaping reactions to flood events remains less discernible, highlighting the need for further research and consideration of factors such as investor beliefs, exposure levels, and insurance policies.

The implications of our findings extend beyond the realm of academia, bearing significance for both policy makers and finance practitioners alike. For policy makers, our research underscores the value of publicly available sources, such as the E-PRTR and Copernicus, in facilitating climate finance analysis. However, our study highlights the need for harmonizing data across countries to enhance the accuracy and comprehensiveness of such sources, particularly in relation to facilities data. Furthermore, the inclusion of additional types of hazards, such as Mediterranean summer storms, in Copernicus could provide a more comprehensive understanding of weather related disasters. These efforts would enable more robust assessments of physical risks and aid policy makers in devising targeted strategies to mitigate the economic impact of weather related disasters.

For finance practitioners, our findings carry implications for investment decisions. The presence of informational barriers and home equity preference in driving market adjustments after weather-related disasters underscores the need for portfolio holders to consider these limitations when formulating their investment strategies. Furthermore, the varying impact of weather-related disasters on market reactions emphasizes the importance of accounting for the specific type of weather related disaster when evaluating investment opportunities. As weather related disasters persist and their impact potentially intensifies, incorporating these insights into investment decision-making could enhance risk management and contribute to more informed asset allocation choices.

Our study lays the groundwork for future research endeavors in the realm of climate finance analysis. We encourage researchers to extend this type of analysis to other countries that possess PRTR locational data, enabling a broader assessment of weather-related natural disasters' impacts on financial markets. Moreover, the exploration of additional types of hazard and their unique characteristics could deepen our understanding of market reactions. Our analysis explicitly account for insurance policies at a national level for specific hazards, nevertheless we recognize their potential influence on reactions to disasters if the insurance coverage is known to investors. The presence of state insurance policies, such as in France, also impacts market dynamics, especially in flood-prone regions. Lastly, we advocate for an interdisciplinary approach that combines insights from finance, climatology, and economics to unravel the intricate interplay of weather related disasters, investor behavior, and financial markets.

In conclusion, our study transcends theoretical frameworks and empirical methodologies to offer insights into the dynamic nexus between weather-related disasters and equity prices. Through a meticulous examination of winter windstorms, wildfires, and floods, we validate established theories, uncover nuanced investor behaviors, and reveal the influence of home equity preference on market adjustments. Our investigation not only contributes to academic discourse but also resonates with policy makers and finance practitioners, illuminating pathways for improved climate finance analysis and informed investment strategies. As societies grapple with the increasing challenges of climate change, our research underscores the pivotal role of financial markets in shaping responses to climatic risks, setting the stage for a more resilient and sustainable future.

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A Boehmer, Musumeci, and Poulsen test statistic

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

$$t_B = \frac{1}{N}\sum_{i=1}^{N} SR_{i,E_t} \Bigg/ \sqrt{\frac{1}{N(N-1)}\sum_{i=1}^{N}\left(SR_{i,E_t} - \sum_{i=1}^{N} SR_{i,E_t}\right)^2} \tag{15}$$

where:

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

$$SR_{i,E_t} = AR_{i,E_t} \Bigg/ \hat{s}_i \sqrt{1 + \frac{1}{T_i} + \frac{\left(R_{m,E_t} - \bar{R_m}\right)^2}{\sum_{t=1}^{T_i}\left(R_{m,t} - \bar{R_m}\right)^2}} \tag{16}$$

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

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

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

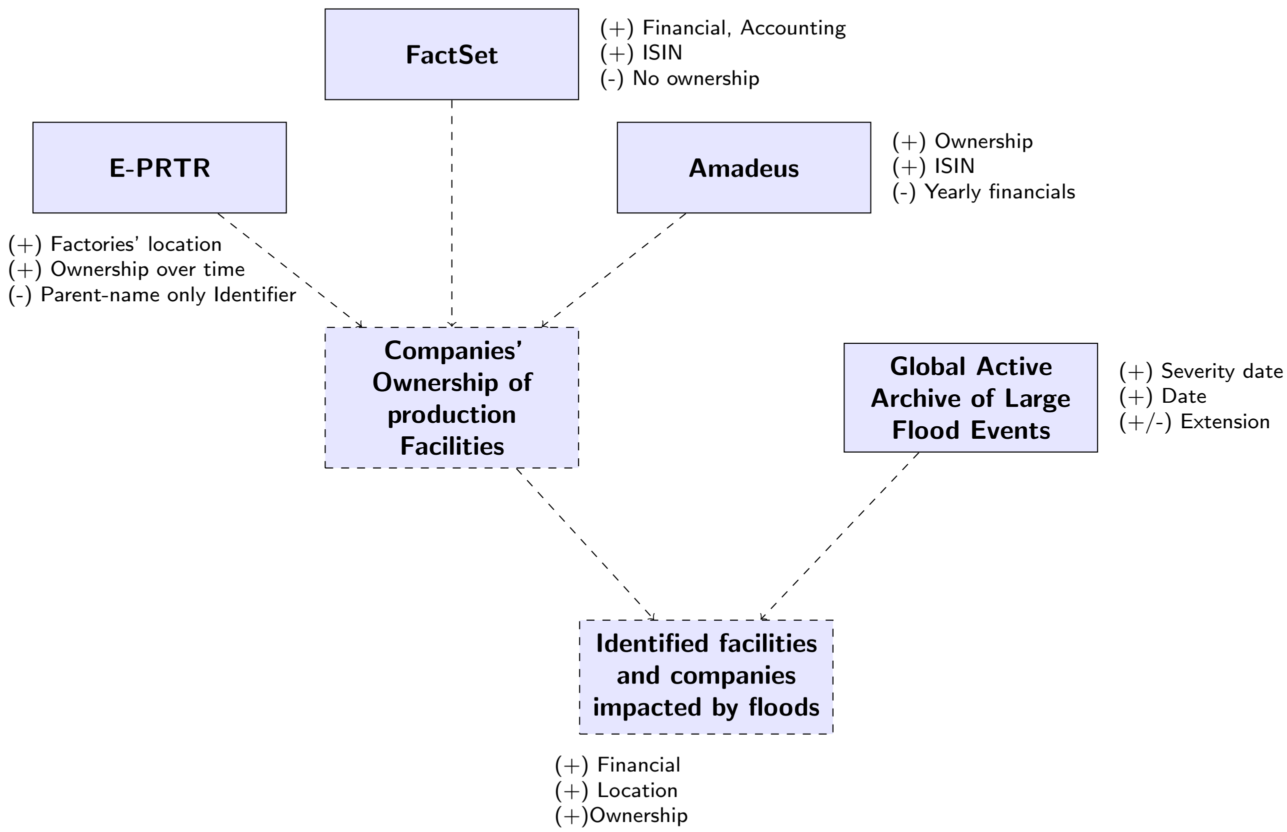


Figure 10. Diverse data sources contribute to the identification strategy: the map shows different sources that charachterize the dataset underlying the analysis: Floods from (Brakenridge, 2021), the (E-PRTR) for the facilities and Amadeus and Factset for the Financials. Dotted lines indicate a merging process. Dotted box borders indicate the resulting dataset of a merging process.

together with the information about how sources are merged together is provided in Figure (10).

From the E-PRTR, we have yearly information about the facilities' ownership. The E-PRTR database provides information about the company name of the direct facility owner, geographical location and whether this facility is still active from 2008 to 2022. From Amadeus (Bureau van Dijk) we derive whether a company is directly listed in the stock exchange or indirectly, thus being a subsidiary of a directly listed company. Amadeus applies the 50% ownership rule to decide which company is the Global- or Domestic Ultimate Owner (GUO/DUO) of a company. Moreover, Factset provides among others information about the different components of a company's balance sheet, the stock prices developments as well as its market capitalization. Finally, from Brakenridge (2021) we know the size, severity, duration, extension and exact geographical location of severe flood events. Where the severity is divided in three classes going from the least severe (e.g., 1) to the most severe (e.g., 2). The concepts of severity is also related to the damages it caused in terms of physical and human capital as well as the recurrence of this type of event. Usually, a severity class of one means that the last time a similar event occurred less than two decades ago while a severity of two indicates that a similar event happened more than a century ago.

To identify companies impacted by floods we first merge companies' information together (E-PRTR, FactSet, Amadeus) and then geographically join them with the extent of geographic regions affected by flooding. At first we merge the names of the facilities' owners from the E-PRTR every year (around 42.000 unique owners which recur several times in the times series) with the names of all subsidiaries included in Amadeus (around 32 Millions unique company names over 2 Vintages 2018-2022). We then merge the resulting database using the ISIN variable included in Amadeus with all other financial information provided by Factset. The resulting database which has the Latitude and Longitude of every single facility is then overlayed with the extent of geographic regions affected by flooding thus giving us the relevant information about which facility in a given year was impacted by a flood.

To combine data we have to meet several choices and overcome considerable challenges. For instance, the only identifier we have to merge production facilities' geographical location from the E-PRTR and subsidiaries from Amadeus are company names. After cleaning for misspelling and special characters we merge only names that match with a 100% rate. With this choice we ensures the absence of false positives that merge together but don't belong to the same company. We achieve a merge quality of around 32% parent company names from the EPRTR. Additionally, to merge the information on the ownership structure on publicly listed companies from Amadeus with the stocks' returns data from Factset we use ISINs' as an identifier. Some ISIN names of the roughly 1200 ISINs we identify do not merge across databases.

C The theory on expected, abnormal and cumulative returns

We compute the OLS coefficients for every company i and event e as in Equation (17) based on the information from Figure(2). Here the time series length equals L_1 and j varies depending on the model used to compute expected returns and indicates the number of explanatory variables used in the regression and a constant.

$$\underbrace{\hat{\beta}_{ie}}_{j\times 1} = (\underbrace{X'_{ie}}_{j\times L_1}\underbrace{X_{ie}}_{L_1\times j})^{-1}\underbrace{X'_{ie}}_{j\times L_1}\underbrace{R_{ie}}_{L_1\times 1} \tag{17}$$

In a second step we compute expected returns for every company and event using equation (18). Here the coefficients are multiplied with the actuals of the explanatory variables during the event window, thus generating the event's counterfactual.

$$\underbrace{E[R_{ie}|X_{ie}]}_{L_2\times 1} = \underbrace{X'_{ie}}_{L_2\times j}\underbrace{\beta_{ie}}_{j\times 1} \tag{18}$$

The matrix $\boldsymbol{X}$ in Equations (17) and (18) changes dimension depending on the model used to compute $E[R_{ie}|X_{ie}]$. For instance, to compute returns with the *Market Model* (MM), the $\boldsymbol{X} = [\boldsymbol{i}, \boldsymbol{R_m} - \boldsymbol{R_f}]$ with the first column being a vector of ones and the second column being the market returns.[8] Similarly, to compute $E[R_{ie}|X_{ie}]$ based on the *Fama-French 3 factor model* (3FM), *Carhart 4 factor model* (4FM) and the *Fama-French 5 factor model* (5FM) then $\boldsymbol{X}$ would become $[\boldsymbol{i}, \boldsymbol{R_m} - \boldsymbol{R_f}, \boldsymbol{SMB}, \boldsymbol{HML}]$, $[\boldsymbol{i}, \boldsymbol{R_m} - \boldsymbol{R_f}, \boldsymbol{SMB}, \boldsymbol{HML}, \boldsymbol{UMD}]$ and $[\boldsymbol{i}, \boldsymbol{R_m} - \boldsymbol{R_f}, \boldsymbol{SMB}, \boldsymbol{HML}, \boldsymbol{RMW}, \boldsymbol{CMA}]$, $\boldsymbol{X}$ respectively [9] $\boldsymbol{SMB}$ (e.g. "small market capitalization minus big") and $\boldsymbol{HML}$ (e.g. "high book-to-market ratio minus low") measure the historic excess returns of small caps over big caps as well as the historic excess returns of value stocks over growth stocks.[10] $\boldsymbol{UMD}$ or *Momentum* is the return difference between a portfolio of the past 12-month return winners and a portfolio of the past 12-month losers. Additionally, while the profitability factor $\boldsymbol{RMW}$ is the difference between the returns of firms with robust (high) and weak (low) operating profitability, the investment factor $\boldsymbol{CMA}$ is the difference between the returns of firms investing conservatively and firms investing aggressively.[11]

D Sample and sources

Our sample is characterized by European public-listed companies that at the time a flood occurred had facilities in a region which was affected by flooding. Understand which facilities have been impacted by a climate hazard is crucial to understand how investors react to this type of event. We cover all countries in the European Union (27) and Great Britain. Overall, we identify 1748 facilities owned by around 600 unique publicly listed companies that have been impacted by climate hazards. When an hazard type (e.g. Flood, Wildfire, Winter storm) recur in a very short time interval for the same company we only consider the first one occurred as this is more likely to update investors' beliefs.[12] In our sample we also consider companies that have been impacted several times by climate hazards therefore the total amount of companies is higher. The event window of our event study is spread on few days before the event depending on the hazard type and 22 days after the event date, hence for our analysis we compute daily returns. The sample period starts in 2014 and finishes end 2021. We provide an overview of how we derive the sample in Appendix (**??**).

D.a Financial measures and stocks' ownership

We obtain data on stock prices, market capitalization, total debt, total assets, book value per share, total tangible assets and short term debt together with institutional stock ownership

[8] Following Kenneth French library explanations, the market is the return on a region's value-weight market portfolio.
[9] The factors are provided on the Kenneth French data Library and are tailored to the European Market.
[10] Further details on how the factors are compute can be found under Description of Fama/French 3 Factors for Developed Markets.
[11] Further details on how the factors are compute can be found under Description of Fama/French 5 Factors for Developed Markets[12] A very short time interval is an interval that is shorter than our estimation window or 90 days.

holdings from *FactSet financial data and analytics* to analyze the financial soundness of companies and value their relevance in terms of market capitalization. The final sample of unique publicly listed companies whose facilities are impacted by hazards varies over hazard type as explained in the following sections, for these we have around 3653 daily returns. This sample is cleaned from financial companies and companies that have less than 10 % float shares.

When checking after the financial soundness of the companies in our sample we find they are mostly overvalued, have a comparably low level of debt financing, feature a middle market capitalization and have a high percentage of tangible assets. Companies are historically overvalued because the market evaluations exceed book values with a median ratio of around 55%. They feature a ratio of tangible assets to total assets of 86%. Moreover, the median debt over assets ratio is 26% and the short debt to debt ratio is of around 20%. The median market capitalization of companies in our sample is historically of € 3.65 bilions which is almost half of the current median market capitalization of the EUROSTOXX 600 Index.

Overall the companies in our sample are not extremely sensible to shocks due to their relatively high financial soundness. The sample historically is not highly leveraged and almost normally distributed with a higher tendency for low indebtedness. Moreover, the companies in our sample feature a book-to-market ratio lower than 1 with fat tails and not strong negative outliers. Thus meaning that in the median many companies show a low book to market ratio and are thus overvalued (Growth stocks) some have a strong positive book-to-market ratio (Value Stocks) and are undervalued. Moreover, in the median the companies show a mid-cap size. These findings motivate our choice to include several factor models to test the validity of our results.

D.b Facilities

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

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

The E-PRTR covers several industrial sectors but not all facilities for every company in the respective sector. In the E-PRTR we find facilities from the energy sector, the production and processing of metals, the mineral industry, the chemical industry, the waste and wastewater management, the paper and wood production and processing,the intensive livestock production and aquaculture, animal and vegetable products from the food and beverage sector and other activities. Facility operators are required to report the amount of waste produced by their facilities if the production quantity of the facility goes above a predefined capacity threshold. For instance, if you own a facility in the ferrous metal foundries, then you should report the amount of waste you produce if your production capacity exceeds 20 tonnes per day. Nevertheless, for some industries in the E-PRTR there is no capacity threshold requirement.[13]

D.c Ownership

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

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

To analyse how investors react to weather-related disasters we find ownership's links between the E-PRTR facility owner and the closest public listed company in terms of ownership structure. We want to understand what is the direct reaction of investors to impacted facilities that are directly or indirectly publicly listed. In our sample we distinguish two different ownership's levels of a public listed company “Home" and“Abroad". Where “Home" is if the impacted facilty is related to a public listed company that is headquartered in the same coutry and “Abroad" when the facility is in a different country than the public companies' headquarters. We take the first publicly listed stock in the ownership chain of a facility and we then compare whether this is located in the same country of the facility or not. The ownership chain that we choose in Amadeus is the 50% of ownership to declare a company's to be the ultimate owner of another one.

In our final sample we count around 600 companies that are publicly listed and linked to a facility in a region that experienced a climate hazard. This list is cleaned from penny stocks (e.g. price less than € 5 before the event) in the estimation period of the event, from some financial companies (not those in the insurance sector) and those that have less than 10% free float.

D.d Weather-related disasters

In our analysis we focus on the hazards that are mostly relevant for Europe in terms of damages: floods, wildfires and winterstorms. These hazards have cose significant damage to European economics in the last decades (EIOPA, 2022). There is also an increasing Trend in terms of damages as highlighted by the 8th EAP report from the European Environmental Agency. In Figure (3) we show that also in the timeframe analysed there seems to be an upward trend in the frequency of climate hazards.

Overall we find 15,798 facilities that are impacted by hazards of these 1,748 are related to public listed entities. In Table (III) we provide an overview of the facilities impacted by hazards as a percentage of the whole sample. Most facilities impacted are in Germany, France, Spain, Italy, United Kingdom and the Netherlands. Additionally, we also show the percentage of facilities impacted that are public listed. Here France, Germany, Italy, United Kingdom and Spain remain relevant while the Netherlands are not anymore among the countries that are mostly impacted. Of the 4,138 facilities that we could link to a publicly listed provider around 42 % are impacted at least once by one of the climate hazards that we analyse.

	All companies			Listed companies		
	Impacted	Total	% Total	Impacted	Total	% Total
Austria	44.0	485.0	0.13	4.0	89.0	0.10
Belgium	714.0	1907.0	2.09	20.0	205.0	0.48
Bulgaria	4.0	5.0	0.01	NaN	NaN	NaN
Croatia	21.0	79.0	0.06	3.0	12.0	0.07
Cyprus	25.0	41.0	0.07	NaN	NaN	NaN
Czechia	34.0	749.0	0.10	1.0	105.0	0.02
Denmark	783.0	1160.0	2.29	10.0	41.0	0.24
Estonia	1.0	115.0	0.00	NaN	NaN	NaN
Finland	6.0	618.0	0.02	2.0	123.0	0.05
France	2736.0	3814.0	8.01	451.0	759.0	10.90
Germany	1496.0	4364.0	4.38	144.0	563.0	3.48
Greece	66.0	185.0	0.19	NaN	NaN	NaN
Hungary	36.0	297.0	0.11	3.0	27.0	0.07
Iceland	9.0	25.0	0.03	NaN	NaN	NaN
Ireland	373.0	524.0	1.09	24.0	37.0	0.58
Italy	2059.0	3236.0	6.03	262.0	383.0	6.33
Lithuania	8.0	50.0	0.02	2.0	6.0	0.05
Luxembourg	31.0	33.0	0.09	1.0	6.0	0.02
Netherlands	1608.0	1826.0	4.71	12.0	41.0	0.29
Poland	256.0	1622.0	0.75	68.0	308.0	1.64
Portugal	134.0	385.0	0.39	13.0	34.0	0.31
Romania	739.0	845.0	2.16	32.0	48.0	0.77
Serbia	8.0	60.0	0.02	NaN	NaN	NaN
Slovenia	8.0	105.0	0.02	NaN	NaN	NaN
Spain	1374.0	3982.0	4.02	116.0	282.0	2.80
Sweden	22.0	710.0	0.06	5.0	117.0	0.12
Switzerland	58.0	182.0	0.17	18.0	57.0	0.43
United Kingdom	3145.0	6758.0	9.21	557.0	895.0	13.46
Total	15798.0	34162.0	46.24	1748.0	4138.0	42.24

Table III. Impacted facilities by Country 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 country. In the first 3 columns we show the impacted facilities, the total number of facilities we match and the percentage of facilities impacted over the total of 32,026.In the last 3 columns we show the same numbers but only for those facilities that have a public listed company in the ownership structure.

We then analyse the amount of facilities belonging to NACE sectors that are highly exposed to physical risk. MSCI in a recent publication showed that sectors as Manufacturing, Utility, Water and Mining are sectors that are highly exposed to climate hazards of different types. These sectors are highly represented in the sample we matched with the E-PRTR. The Manufacturing sectors is around 20% of all facilities that are owned by public entities and are impacted by hazards. The other sectors also characterized the majority of facilities impacted. This analysis is presented in Table (IV) we provide an overview of the facilities impacted by hazards as a percentage of the whole sample.

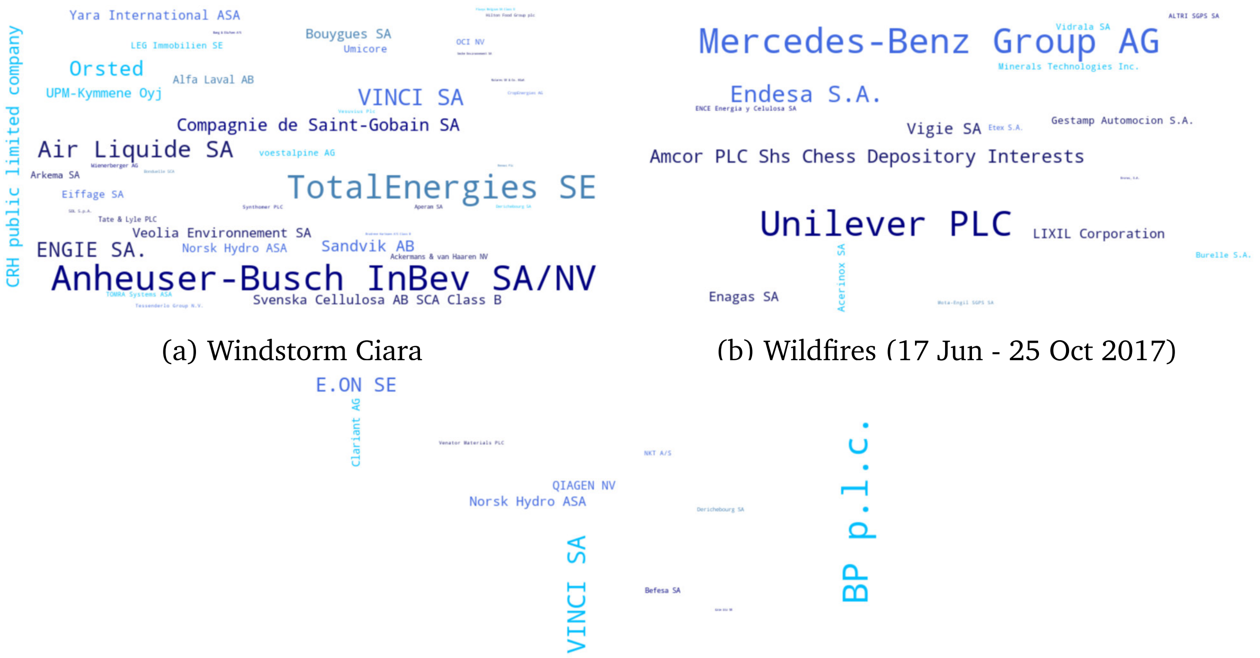
	All companies			Listed companies		
	Impacted	Total	% Total	Impacted	Total	% Total
ADMINISTRATIVE	570.0	1163.0	1.78	52.0	90.0	1.29
AGRICULTURE	282.0	904.0	0.88	10.0	31.0	0.25
COMMUNICATION	99.0	233.0	0.31	18.0	44.0	0.45
CONSTRUCTION	356.0	762.0	1.11	18.0	46.0	0.45
EDUCATION	11.0	16.0	0.03	NaN	NaN	NaN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

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

In the following sections we explain how we derived the data used to plot Figure (3) and compute Tablee (III) analysing in detail the sources and the assumption we did to derive them.

D.e Companies in the Case Studies

In Sub-Figure (11a) we include the names of companies by market capitalization that are included in the case study on Storm Ciara in February 2020. Here we see that the companies impacted are mostly related to the utility as manufacturing sectors such as Air Liquide, Anheuser-Busch InBev and Engie. Additionally, in Sub-Figure (11b) we show the names of companies impacted by the wildfires in Portugal and Spain in summer 2017. Here, we can find regional companies such as Endesa and international ones such as Mercedes-Benz Group. In Sub-Figure (11c) we also included the names of companies included in the case study for the summer floods in July 2021. Here we find utility companies such as E.ON or BP or construction related companies such as Vinci SA.



(a) Windstorm Ciara

(b) Wildfires (17 Jun - 25 Oct 2017)

(c) Summer floods (13 - 15 Jul 2021)

Figure 11. Companies impacted by different hazards in the Case Studies: In Sub-Figure (11a) we show the names of companies impacted by windstorm Ciara in February 2020. The higher the font size the higher the market capitalization of the company. In Sub-Figure (11b) we show the names of companies impacted by wildfires in Portugal and Spain from February June to October 2017. In Sub-Figure (11c) we show the names of companies impacted by the summer floods in 2021. The higher the font size the higher the market cap of the company.

D.f Winter Windstorms

We compute the exposure of companies to winter windstorms in Europe using the windstorms' footprints from the Climate Data Store provided by the Copernicus Programme.[14] The dataset provides climatological indicators on European winter windstorms and their economic impact derived from ERA5 reanalysis. We focus on winter windstorm footprints as they are defined as the maximum 3-second 10-m wind gust speed (in m s-1) over a 72-hour period at each model grid point for a significant winter storm. As such, a storm footprint shows the spatial distribution of maximum wind gust speed for a storm crossing the area of interest.

The C3S storm footprint dataset consists of footprints from all identified winter storms, by the Storm Tracking module, over the period 1979-2021 (van den Brink, 2020). Some years are excluded from the dataset as they did not exceeded the selection criteria threshold of 25m/s 10m winds over land using a 3-degree sampling region. For this reason our sample misses year 2018 and 2019. Due to the timeframe considered in our analysis we only include those storm footprints from 2014 to 2021. Figure (12) shows all areas and an relative windstorm speed of all windstorms that impacted Europe from 2014 to 2021. In Sub-Figure (12b) we show the footprint of Storm Ciara that impacted Europe from February 7 to February 11 2020 and had particular damaging effects on the impacted areas.

[14] You can find more information under Copernicus Programme

(a) Windstorms (2014-2021)

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

Figure 12. Winter windstorms in Europe from 2014 to 2021: In Sub-Figure (12), we show the areas and intensity of winter windstorms that impacted Europe from 2014 to 2021. In Sub-Figure (12b) we show the area that was impacted by the winter windstorm Ciara from February 7 to 11 2020. The different colors show different levels of 10 Minutes Wind Speed in the different areas. The darker the surface the stronger the wind speed.

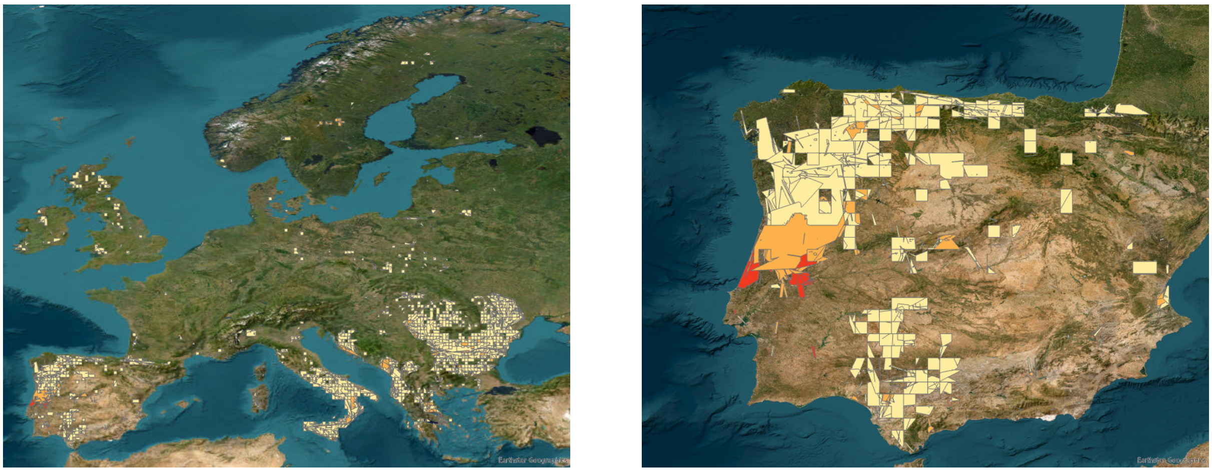
Our sample consists of 16 windstorms, which are heterogeneously distributed throughout Northern Europe as shown in Figure (12). The average historical the maximum 3-second 10m wind gust over time and events is 34 km/H. A windspeed of above 30 mk/h is considered to be damaging for most European buildings as analysed in detail in a recent scientifc report (Prahl et al., 2016) . The event date is considered the one of landfall as suggested in (Lanfear et al., 2019).

We identify 181 unique public listed companies whose facilities are impacted by winter windstorms. The names of the companies impacted by winter windstorms are included in Sub-Figure (4a). Many highly capitalized companies are included in the sample such as Total Energies, Novartis and General Electric. Additionally, in Sub-Figure (11a) we include the names of companies by market capitalization that are included in the case study on Storm Ciara in February 2020. Here we see that the companies impacted are mostly related to the utility as manufacturing sectors such as Air Liquide, Anheuser-Busch InBev and Engie.

D.g Wildfires

We compute the exposure of companies to wildfires using Active fire historical data and burned area pixels. First we find the date and location of Active fires from Active Fire Data provided by the NASA Earth Data Open Access for Science. This data provides information from 2000 to present on active fire data. The Fire Information for Resource Management System (FIRMS) was developed to provide near real-time active fire locations to natural resource managers that faced challenges obtaining timely satellite-derived fire information. We merge this information on monthly burned areas pixels' estimates from the Climate Data Store provided by the Copernicus Programme. The Burned Area products provide global information of total burned area (BA) at pixel and grid scale. The BA is identified with the date of first detection of the burned signal in the case of the pixel product, and with the total BA per grid cell in the case of the grid product. The products were obtained through the analysis of reflectance changes from medium resolution sensors (Terra MODIS, Sentinel-3 OLCI), supported by the use of MODIS thermal information. [15]

Active fires provide us the exact timing, type and location of an active fire while burned areas give us the extent of damage caused by the event. In Figure (**??**) we provide an overview of the regions impacted from Wildfires since 2014 to 2021. In total we identified 2332 wildfires since 2014 and wekept those that have been characterized as wildfire from FIRMS with a confidence level of 80 % at least. As can be seen in the picture the case study that we use for our analysis in Sub-Figure (13b) has been one of the most damaging in terms of burned area in the EU since 2014.



(a) Wildfires (2014-2021) (b) Wildfires (17 Jun - 25 Oct 2017)

Wildfires in Europe from 2014 to 2021: In Sub-Figure (13a), we show the areas and extent of median burnt area of wildfires that impacted Europe from 2014 to 2021. In Sub-Figure (13b) we show the area that was impacted by the wildfires in Portugal and Spain from February June to October 2017. The different colors show different levels of burnt area by pixel. The darker the color the wider the median burned area by pixel

With our methodology we are able to identify 136 unique public listed companies that are impacted by wildfires over the sample period. An example of company names impacted by wildfires in Europe since 2014 is contained in Figure (4b). Here we can see some highly capitalized companies in the sample such as Unilever, ExxonMobil and Nestle. Additionally, in Sub-Figure (11b) we show the names of companies impacted by the wildfires in Portugal and Spain in summer 2017. Here we can find regional companies such as Endesa and international ones such as Mercedes-Benz Group.

[15] You can find more information under FIRMS, Copernicus burned area

D.h Floods

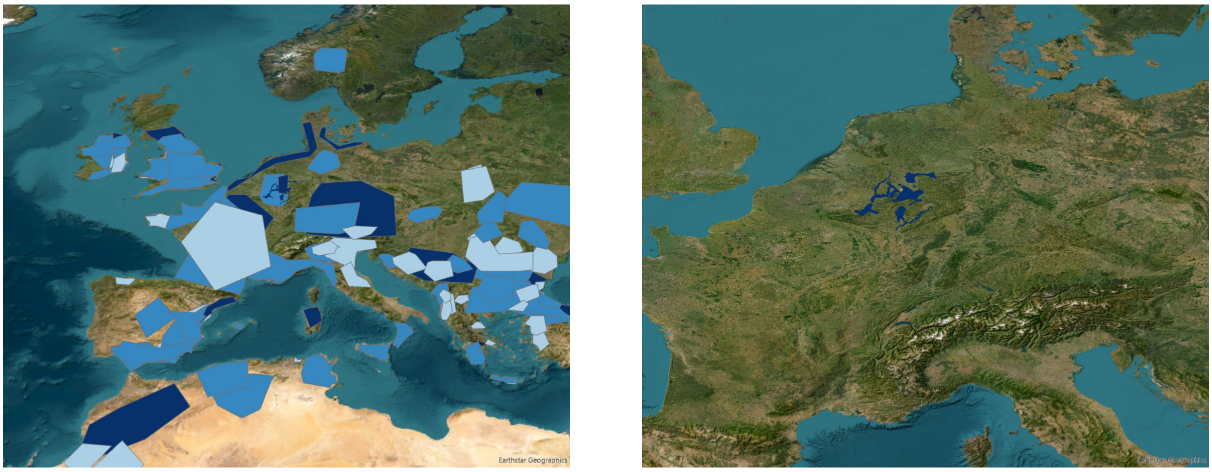
To compute the exposure of companies to floods we use information provided in form of polygons by Brakenridge (2021). The database provides global coverage of the strongest flood events happened in history and an estimate of the land surface coverage. The floods are listed by the severity of the event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

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

Our flood sample consists of 68 flood events, which are heterogeneously distributed. 35 events have a severity class of 1.5, 27 events of 1.0 and 6 events with a severity class of 2.0.The geographic distribution of events is very heterogeneous. From Figure (??) we can see that most of the events take place in central and southern Europe. In the specific 10 have Spain as the main country, 8 Italy, 10 France, 7 in Greece and 5 in the United Kingdom among others. In Sub-Figure (14b) we also include a picture for the case study on the summer floods in the Belgium, germany and the Netherlands in July 2021, which impacted several regions. The event is classified as event of severity class 2.

With our methods we identify unique 438 companies whose facilities have been impacted by floods over time. Since we only consider companies that have at least 10 % of free float and and are non financial companies this number is lower than the one we would have not accounting for that. Nevertheless, this number might be lower in fact as we usually exclude out of the event studies those companies that don't have a price above 5 € in the estimation period. Some companies might be impacted several times and in different locations, such that the number of companies in the event study is usually higher than this estimate.

The names of the companies impacted by floods and listed by market capitalization are shown in Figure (4c) which shows the names of companies in our sample by market capitalization. Thus, meaning the bigger font sizes are related to a higher historical average market capitalization. There are some highly capitalized companies and international companies in our sample such as Johnson & Johnson, Nestle, Bayer AG, Total Energies and Astrazeneca that characterize our sample. In Sub-Figure (11c) we also included the names of companies included in the case study for the summer floods in July 2021. Here we find



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

Floods in Europe from 2014 to 2021: In Sub-Figure (??), we show the areas and severity of floods that impacted Europe from 2014 to 2021. In Sub-Figure (14b) we show the area that was impacted by the summer floods in the Belgium, Germany and the Netherlands in Jul 2021. The different colors show different levels of severity by polygon. The darker the lower the recurrence of such a flood event in the area.

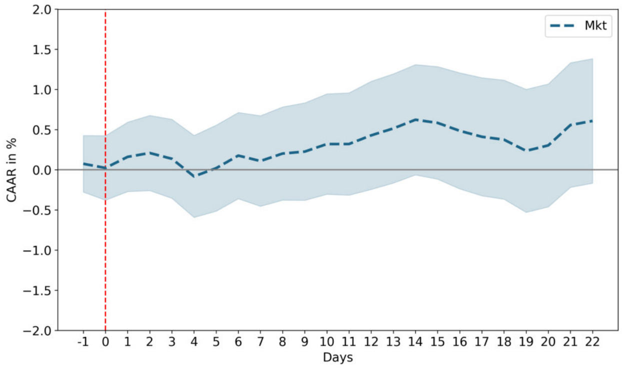
utlitiy companies such as E.ON or BP or construction related companies such Vinci SA.

E Additional Results

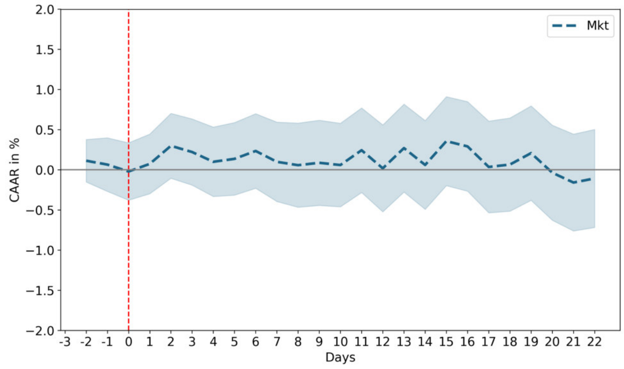
E.a CAAR: Wildfires and Floods

When we focus on wildfires we do not observe a negative and significant trend around the event date, CAAR appear to turn positive after approximately 15 days (see Sub-Figure (15a)). The result is broadly in line with the pattern identified in our individual case study and with the findings from the literature (Huynh and Xia, 2021). Part is also due to an empirical setting for wildfires that is not yet fully identifying the more relevant events. Interestingly, when stratifying by facility location, we find that companies whose impacted facilities are in the same country as their stock display stronger positive cumulative returns (see Sub-Figure (15c)) compared to those with facilities abroad (see Sub-Figure (15e)). This finding shows that there are informational distance barriers in place that do not allow investors to correctly account for the impact of this risk type.

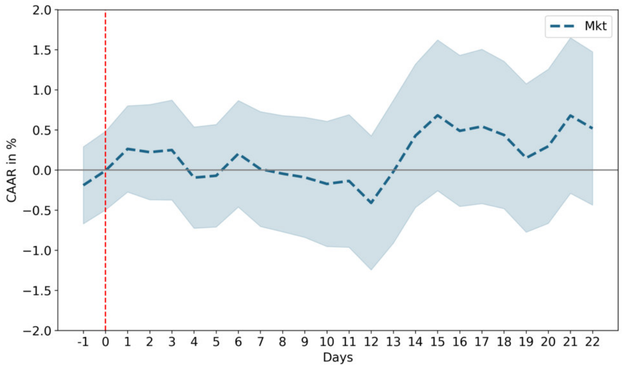
In the context of floods, our analysis reveals intriguing dynamics. Although an initial downward adjustment in CAAR is observable around the event date, this adjustment fails to achieve statistical significance (see Sub-Figures 15b). This implies that the market's reaction to flood events is not substantially different from zero. However, upon extending the analysis to 22 days post-event, we observe a subtle shift toward slightly positive cumulative abnormal returns. This phenomenon holds true across all three categories: all companies, those whose impacted facilities are in the same country, and those with facilities abroad (see Sub-Figures (15d) and (15f)). The intricacies of these responses underscore the nuanced nature of market



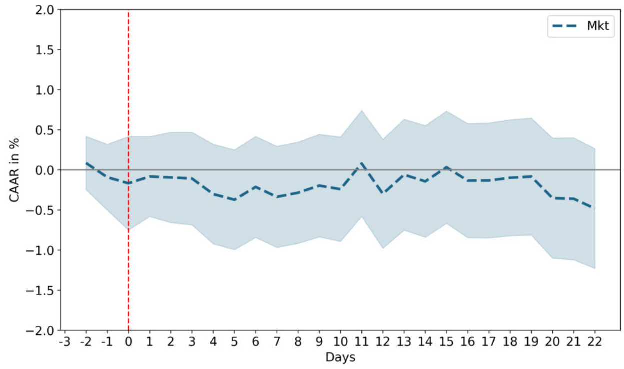
(a) Wildfires



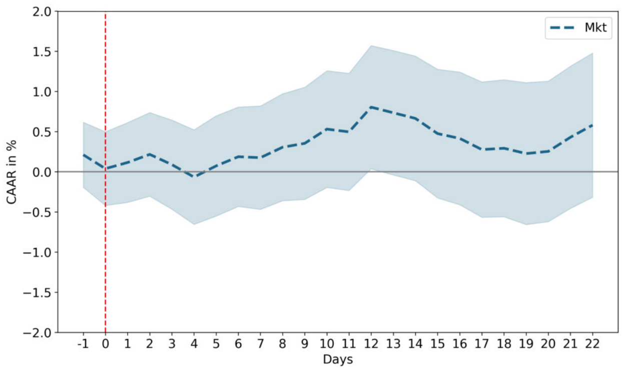
(b) Floods



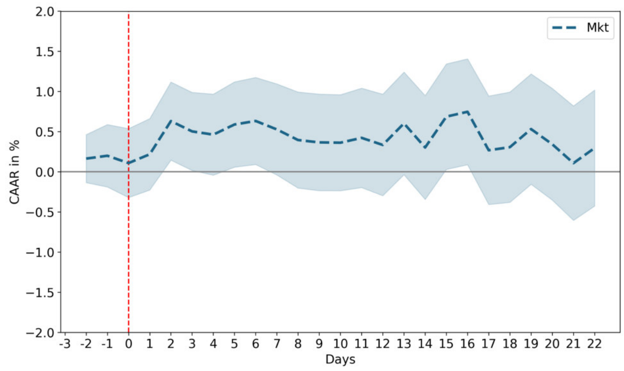
(c) Wildfires: Home



(d) Floods: Home



(e) Wildfires: Abroad



(f) Floods: Abroad

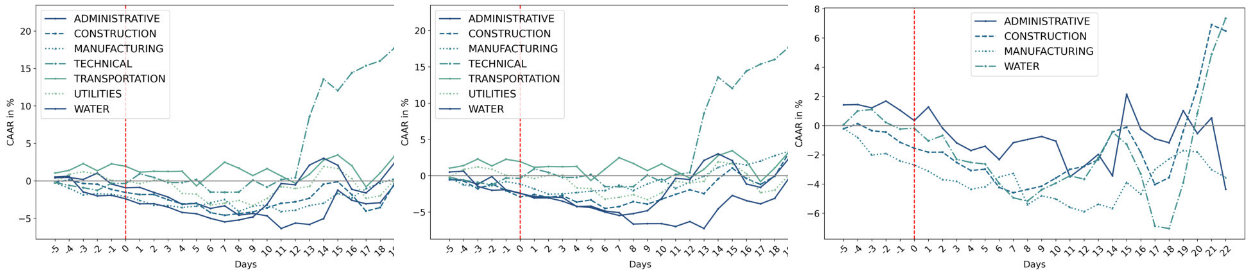
Figure 15. Cumulative Average Abnormal Returns (CAAR) by Hazard type: In Sub-Figures (15a,15b) we depict CAAR for companies impacted wildfires and floods independent of the location of the facility compared to its headquarters. In Sub-Figures (15c,15d) we depict CAAR for companies impacted by wildfires and floods whose impacted facilities are located in the same country of the headquarters. Finally, in Sub-Figures (15e,15f) we depict CAAR for companies impacted by wildfires and floods whose impacted facilities are located in a different country than the one of the headquarters. The Y-axis of each figure represents CAAR in %, and the X-axis days from the event, where positive values are after event beginning and negative before.

adjustments in the wake of flood events, where investors do not update their beliefs on flood risks after event occurrence as highlighted in (Giglio et al., 2023).

E.b Industry analysis

E.b.2 The Case studies

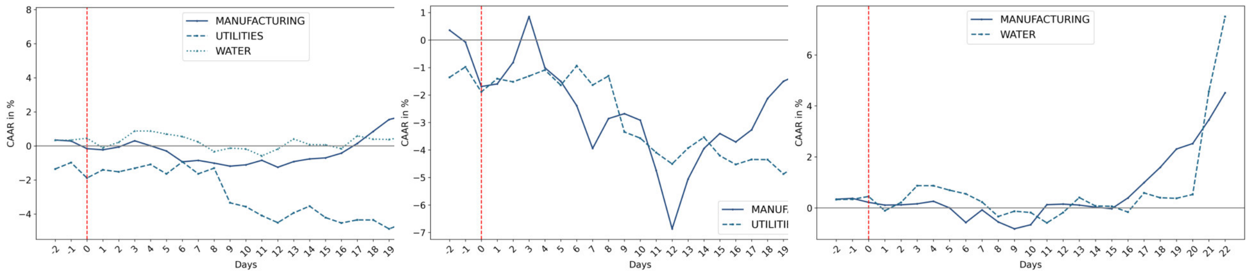
Windstorm Ciara 2020 In Figure 16 we notice that CAAR are mostly negative and persistent over a longer period, particularly for three main NACE categories: Construction, Manufacturing and Water supply related activities (see Sub-figures 16a,16b and 16c).[16]



(a) All (b) Home (c) Abroad

Figure 16. CAAR for Windstorm Ciara February 2020 by Industry: In Sub-Figure (5a), we depict CAAR for companies impacted by winter windstorm Ciara which formed on 3 February 2020 and dissipated on 16 February 2020. In Sub-Figures (16a),(16b) and (16c) we compure the same CAAR but by NACE economic section breakdown. The Y-axis of each figure represents CAAR in %, and the X-axis days from the event, where positive values are after event beginning and negative before.

Wildfires summer season 2017



(a) All (b) Home (c) Abroad

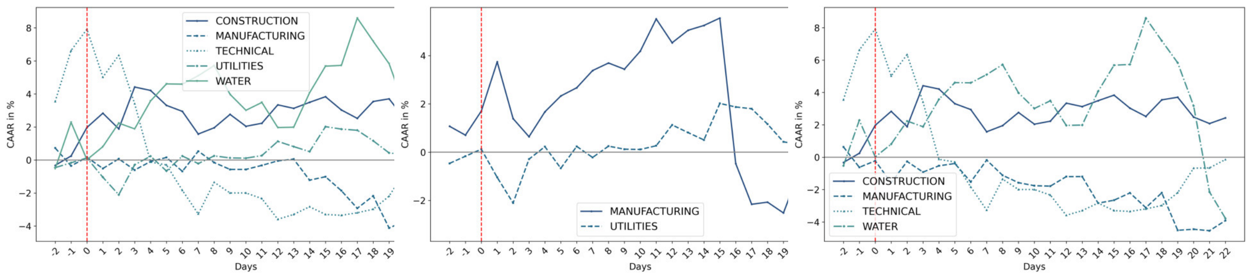
Figure 17. CAAR for the Wildfire Season in Portugal and Spain 2017: The Y-axis of each figure represents CAAR in %, and the X-axis days from the event, where positive values are after event beginning and negative before.In Sub-Figures (17a),(17b) and (17c) we compute CAAR by NACE economic section breakdown.

In a breakdown by NACE sector we find that facilities in the same industry are differently impacted depending on whether they are located “Home" or “Abroad". As only 13 companies are impacted by the wildfires we further divide them in industries to see whether investors differently perceive companies belonging to the same industry depending on the facilities' location. By comparing Sub-Figures (17b) and (17c) we see that companies belonging to the manufacturing economic section are more impacted if the location of the facility impacted is in the same country of the headquarters. This result hints to discrepancies of investors' surprise depending on the facilities' locations.

Northern European Summer floods 2021

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

After a breakdown by economic activity, we find that some sectors are more impacted than others when exposed to floods. Overall, independent from the location of the facility, companies in the manufacturing or professional, scientific and technical activities are negatively impacted by floods (See Sub-Figure (18a). When accounting for the location of the facility compared to the headquarters we find that investors react differently, particularly in the manufacturing sector. Comparing Sub-Figure (18b) and Sub-Figure (18c), we can hint to some signs of investors' overreaction if the facility is located in the same country, with then a considerable drop after after 15 days from the event occurrence. This is probably so as the extent of the damages becomes clearer to home country investors those decreasing the impact related uncertainty described by Kruttli et al. (2023). However, the impact is not as strong as when the facility is located abroad suggesting that home investors have a comparative advantage in gathering this observation. On the other hand foreign investors experience a negative surprise as of the event date.



(a) Floods July 2021 (b) Floods July 2021: Home (c) Floods July 2021: Abroad

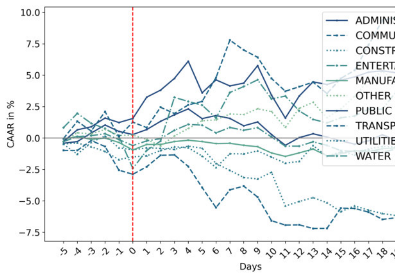
CAAR for the summer floods in Central Europe July 2021: In Sub-Figure (7a), we depict CAAR for companies impacted by the summer floods in Germany, Belgium and the Netherlands from 13 to 15 July 2021 independent of the location of the facility compared to its headquarters, dendent on whether the facilities impacted were in the same country and for those companies whose facilities are located abroad. The Y-axis of each figure represents CAAR in %, and the X-axis days from the event, where positive values are after event beginning and negative before. In Sub-Figures (18a),(18b) and (18c) we compute CAAR but by NACE economic section breakdown.

E.b.2 The whole sample

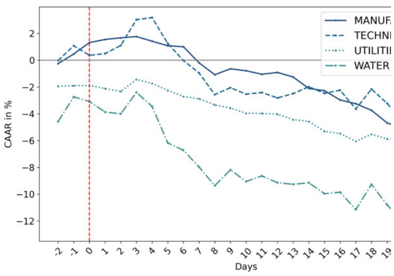
Next we analyse whether the industry belonging of the company impacted plays a role for investors' reaction. In the specific we expect to see a stronger reaction for industry that have a material exposure to physical risks. For instance those highlighted in the (Dunz et al., 2021) , such as manufacturing, construction etc. . We also expect that if the impacted facility is located abroad than similar thoughts as before apply.

The industries that are mostly impacted by winter wind storms are manufacturing, utilities, construction and transportation. Eyeballing Sub-Figures (19a, 19d and 19g) we can see that the industries that are mostly impacted are manufacturing, utilities, construction and transportation. Nevertheless, it seems that when the facility is located abroad investor's surprise is stronger and more negative.

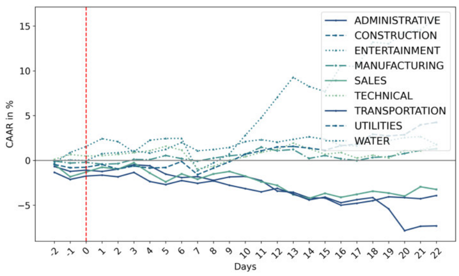
As for wildfires we can see that the economic activity most exposed to a negative market



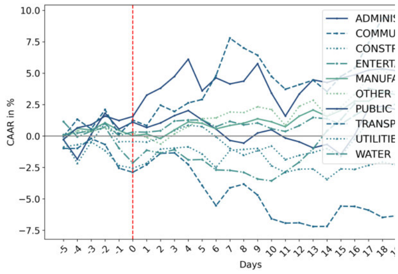
(a) Windstorms



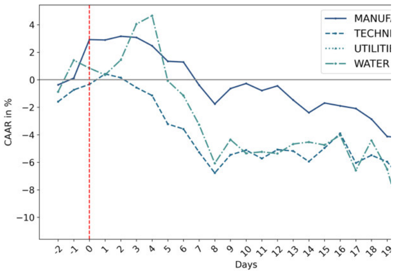
(b) Wildfires



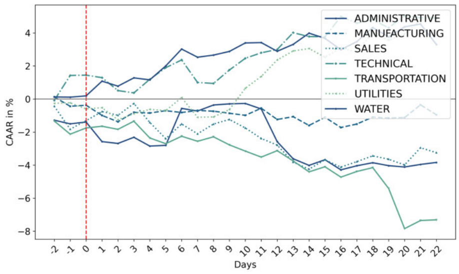
(c) Floods



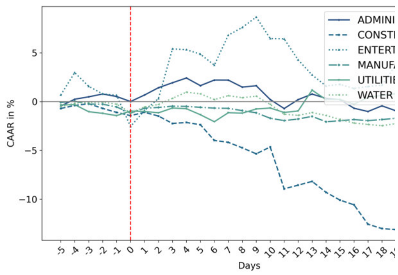
(d) Windstorms: Home



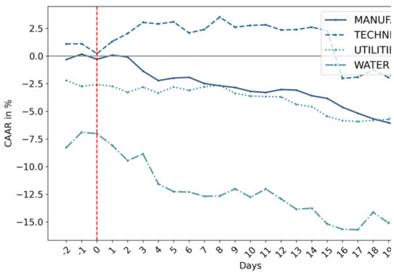
(e) Wildfires: Home



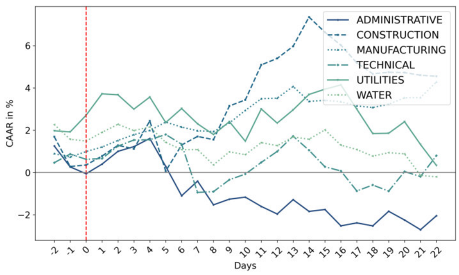
(f) Floods: Home



(g) Windstorms: Abroad



(h) Wildfires: Abroad



(i) Floods: Abroad

Figure 19. Cumulative Average Abnormal Returns (CAAR) by Hazard type: In Sub-Figures (19a,19b,19c) we depict CAAR for companies impacted by winter windstorms, wildfires and floods independent of the location of the facility compared to its headquarters. In Sub-Figures (19d,19e,19f) we depict CAAR for companies impacted by winter windstorms, wildfires and floods whose impacted facilities are located in the same country of the headquarters. Finally, in Sub-Figures (19g,19h, 19i) we depict CAAR for companies impacted by winter windstorms, wildfires and floods whose impacted facilities are located in a different country than the one of the headquarters.The Y-axis of each figure represents CAAR in %, and the X-axis days from the event, where positive values are after event beginning and negative before.

shock is manufacturing. Eyeballing Sub-Figures (19b, 19e and 19h) leads to very similar results depending on whether the facilities are located abroad and home.

Finally, for floods transportation related activities seem to sufer more from weather related disasters. Additionally, if the facility is located abroad, investors' seem not to be surprised from the event's occurrence. This does not hold when the facility is located in the same country of the headquarters. These results are reported in Sub-Figures (19c, 19f and 19i).

E.c CAAR Tables

	ALL				HOME				FOREIGN			
t	Mkt	3F	4F	5F	Mkt	3F	4F	5F	Mkt	3F	4F	5F
CAAR$_{t=(-5)}$	-0.09	-0.16	-0.13	-0.1	-0.19	-0.18	-0.22	-0.1	0.0	-0.09	-0.01	-0.04
	(-0.41)	(-0.69)	(-0.37)	(-0.66)	(-0.5)	(-0.61)	(-0.49)	(-0.44)	(0.35)	(0.04)	(0.77)	(-0.05)
CAAR$_{t=(-4)}$	-0.44	-0.55	-0.51	-0.41	-0.36	-0.36	-0.4	-0.26	-0.48	-0.61	-0.51	-0.44
	(-1.66)	(-2.04)	(-1.76)	(-2.09)	(-0.86)	(-0.98)	(-0.93)	(-0.87)	(-1.57)	(-2.12)	(-1.54)	(-1.54)
CAAR$_{t=(-3)}$	-1.16	-1.21	-1.19	-1.06	-0.75	-0.71	-0.74	-0.64	-1.52	-1.58	-1.52	-1.35
	(-2.93)	(-2.98)	(-3.03)	(-2.96)	(-1.2)	(-1.26)	(-1.28)	(-1.18)	(-2.92)	(-3.0)	(-3.11)	(-2.49)
CAAR$_{t=(-2)}$	-1.05	-1.05	-1.04	-1.02	-0.63	-0.56	-0.57	-0.31	-1.46	-1.43	-1.41	-1.63
	(-2.53)	(-2.63)	(-2.65)	(-2.53)	(-1.14)	(-1.22)	(-1.24)	(-0.88)	(-2.06)	(-2.03)	(-2.01)	(-2.15)
CAAR$_{t=(-1)}$	-1.31	-1.27	-1.27	-1.32	-0.71	-0.61	-0.62	-0.27	-1.96	-1.87	-1.85	-2.33
	(-2.32)	(-2.47)	(-2.47)	(-2.45)	(-1.17)	(-1.37)	(-1.4)	(-0.83)	(-2.34)	(-2.16)	(-2.15)	(-2.49)
CAAR$_{t=(0)}$	-1.64	-1.67	-1.63	-1.73	-1.1	-1.03	-1.07	-0.61	-2.23	-2.24	-2.14	-2.82
	(-2.54)	(-2.73)	(-2.67)	(-2.67)	(-1.73)	(-1.96)	(-2.07)	(-1.28)	(-2.61)	(-2.5)	(-2.37)	(-2.83)
CAAR$_{t=(1)}$	-2.14	-2.09	-2.08	-2.19	-1.7	-1.62	-1.64	-1.12	-2.58	-2.49	-2.46	-3.24
	(-2.91)	(-3.02)	(-3.01)	(-2.86)	(-2.03)	(-2.19)	(-2.23)	(-1.56)	(-2.6)	(-2.49)	(-2.44)	(-2.85)
CAAR$_{t=(2)}$	-2.6	-2.42	-2.45	-2.53	-1.97	-1.86	-1.83	-1.46	-3.2	-2.94	-3.0	-3.59
	(-3.58)	(-3.5)	(-3.49)	(-3.36)	(-2.13)	(-2.27)	(-2.2)	(-1.75)	(-3.6)	(-3.24)	(-3.26)	(-3.5)
CAAR$_{t=(3)}$	-2.76	-2.54	-2.57	-2.71	-2.06	-1.93	-1.9	-1.47	-3.51	-3.18	-3.26	-4.02
	(-3.98)	(-3.74)	(-3.73)	(-3.52)	(-2.5)	(-2.58)	(-2.48)	(-1.81)	(-4.28)	(-3.55)	(-3.54)	(-3.96)
CAAR$_{t=(4)}$	-3.22	-2.93	-2.98	-3.0	-2.49	-2.34	-2.29	-1.84	-4.02	-3.59	-3.71	-4.28
	(-4.4)	(-3.96)	(-3.96)	(-3.62)	(-2.87)	(-2.79)	(-2.7)	(-2.01)	(-5.5)	(-4.46)	(-4.32)	(-4.48)
CAAR$_{t=(5)}$	-3.16	-2.83	-2.89	-2.94	-2.52	-2.36	-2.3	-1.84	-3.85	-3.37	-3.51	-4.16
	(-4.42)	(-3.88)	(-3.92)	(-3.59)	(-3.11)	(-2.87)	(-2.81)	(-2.05)	(-5.16)	(-3.91)	(-3.89)	(-4.19)
CAAR$_{t=(6)}$	-3.05	-2.8	-2.82	-2.9	-2.88	-2.73	-2.72	-2.24	-3.36	-2.99	-3.03	-3.74
	(-4.06)	(-3.69)	(-3.74)	(-3.47)	(-3.05)	(-2.87)	(-2.88)	(-2.14)	(-4.55)	(-3.44)	(-3.5)	(-4.03)
CAAR$_{t=(7)}$	-2.7	-2.61	-2.56	-2.64	-2.53	-2.43	-2.47	-1.95	-3.08	-2.93	-2.83	-3.51
	(-3.43)	(-3.36)	(-3.24)	(-3.17)	(-2.61)	(-2.57)	(-2.5)	(-1.92)	(-3.51)	(-3.15)	(-2.87)	(-3.45)
CAAR$_{t=(8)}$	-3.99	-3.78	-3.76	-3.71	-3.09	-2.96	-2.97	-2.55	-5.02	-4.71	-4.68	-5.0
	(-4.3)	(-4.03)	(-4.02)	(-3.67)	(-2.89)	(-2.81)	(-2.81)	(-2.25)	(-3.78)	(-3.23)	(-3.26)	(-3.23)
CAAR$_{t=(9)}$	-3.49	-3.29	-3.27	-3.24	-2.72	-2.6	-2.62	-2.11	-4.4	-4.11	-4.05	-4.53
	(-3.36)	(-3.21)	(-3.17)	(-2.83)	(-2.06)	(-1.99)	(-1.97)	(-1.44)	(-3.33)	(-2.87)	(-2.91)	(-2.9)
CAAR$_{t=(10)}$	-3.23	-3.01	-2.96	-3.04	-2.0	-1.82	-1.87	-1.32	-4.64	-4.28	-4.17	-4.89
	(-2.59)	(-2.51)	(-2.42)	(-2.27)	(-1.38)	(-1.39)	(-1.34)	(-0.96)	(-3.51)	(-2.83)	(-2.88)	(-2.99)
CAAR$_{t=(11)}$	-3.74	-3.54	-3.46	-3.61	-2.15	-1.98	-2.06	-1.59	-5.42	-5.1	-4.93	-5.68
	(-2.73)	(-2.73)	(-2.61)	(-2.58)	(-1.4)	(-1.51)	(-1.52)	(-1.21)	(-3.92)	(-3.28)	(-3.37)	(-3.44)
CAAR$_{t=(12)}$	-3.66	-3.42	-3.36	-3.51	-1.77	-1.56	-1.64	-1.24	-5.65	-5.27	-5.11	-5.8
	(-2.6)	(-2.63)	(-2.51)	(-2.52)	(-1.22)	(-1.38)	(-1.39)	(-1.14)	(-4.1)	(-3.25)	(-3.31)	(-3.44)
CAAR$_{t=(13)}$	-3.0	-2.79	-2.68	-2.78	-1.11	-0.89	-1.0	-0.68	-5.01	-4.66	-4.41	-4.87
	(-2.06)	(-2.11)	(-1.88)	(-2.0)	(-0.85)	(-1.0)	(-0.95)	(-0.85)	(-3.97)	(-3.09)	(-3.16)	(-3.17)
CAAR$_{t=(14)}$	-2.43	-2.23	-2.1	-2.11	0.47	0.7	0.56	0.75	-5.43	-5.08	-4.78	-4.91
	(-1.39)	(-1.36)	(-1.09)	(-1.28)	(-0.2)	(-0.24)	(-0.16)	(-0.19)	(-3.66)	(-2.93)	(-3.06)	(-2.85)
CAAR$_{t=(15)}$	-1.2	-1.24	-1.02	-1.18	0.88	1.04	0.82	1.21	-3.37	-3.36	-2.86	-3.44
	(-0.87)	(-1.04)	(-0.56)	(-0.99)	(-0.01)	(-0.12)	(0.03)	(0.01)	(-2.71)	(-2.33)	(-2.32)	(-2.37)
CAAR$_{t=(16)}$	-2.09	-2.4	-2.09	-2.27	-0.01	0.02	-0.31	0.2	-4.37	-4.75	-4.02	-4.67
	(-1.56)	(-1.91)	(-1.22)	(-1.82)	(-0.5)	(-0.74)	(-0.51)	(-0.59)	(-2.9)	(-2.92)	(-3.01)	(-2.86)
CAAR$_{t=(17)}$	-1.62	-2.0	-1.67	-1.9	-0.53	-0.47	-0.82	-0.23	-3.08	-3.54	-2.76	-3.6
	(-1.28)	(-1.73)	(-0.94)	(-1.62)	(-0.73)	(-1.1)	(-0.74)	(-0.87)	(-2.36)	(-2.35)	(-2.11)	(-2.36)
CAAR$_{t=(18)}$	-0.92	-1.45	-1.05	-1.44	0.29	0.32	-0.1	0.69	-2.53	-3.18	-2.25	-3.55
	(-0.68)	(-1.24)	(-0.32)	(-1.18)	(-0.2)	(-0.59)	(-0.17)	(-0.28)	(-1.99)	(-2.08)	(-1.45)	(-2.23)
CAAR$_{t=(19)}$	0.14	-0.39	0.03	-0.28	1.83	1.87	1.42	2.15	-1.79	-2.45	-1.45	-2.53
	(0.09)	(-0.4)	(0.37)	(-0.35)	(0.52)	(0.34)	(0.46)	(0.53)	(-1.39)	(-1.48)	(-0.73)	(-1.56)
CAAR$_{t=(20)}$	0.95	-0.23	0.47	-0.09	3.65	3.49	2.74	3.66	-1.86	-3.42	-1.75	-3.3
	(0.64)	(-0.08)	(0.75)	(-0.04)	(0.95)	(0.65)	(0.69)	(0.77)	(-1.07)	(-1.58)	(-0.35)	(-1.56)
CAAR$_{t=(21)}$	0.62	-0.41	0.26	-0.22	4.37	4.26	3.55	4.56	-2.86	-4.2	-2.62	-4.13
	(0.43)	(-0.2)	(0.61)	(-0.15)	(1.17)	(0.91)	(0.89)	(1.07)	(-1.65)	(-1.95)	(-0.92)	(-1.96)
CAAR$_{t=(22)}$	0.45	-0.44	0.19	-0.53	4.64	4.62	3.94	5.01	-3.55	-4.69	-3.18	-5.28
	(0.49)	(-0.03)	(0.66)	(-0.08)	(1.37)	(1.21)	(1.01)	(1.32)	(-1.74)	(-1.83)	(-0.96)	(-2.03)
N	39	39	39	39	21	21	21	21	20	20	20	20

Table V. Winterstorms: CAAR for storm Ciara in February 2020: In Table (V) we present unweighted average cumulative average abnormal excess abnormal returns (CAAR) in percentage points for the winter windstorm Ciara in February 2020. CAAR are computed using expected returns are from the market model (Mkt) and the factor models ($3F$,$4F$,$5F$). The variance for the test statistic is computed over the cross section of cumulative abnormal returns (CAR) using the variance estimate by (Boehmer et al., 1991). The resulting t_{BMP} statistics are normally distributed and presented in brackets below the CAAR. N is the number of companies in the cross section and t is the day from the event date. Negative values are before and positive after the event date. The cross section of securities i CAAR is derived over several events. Returns over weekends are omitted, as such an event date during the weekend will be on the next trading day in the analysis. The columns under ALL, are all possible events related to the climate hazard independent from the facility location with respects to the headquarters. HOME means that we only compute CAAR for those companies, whose impacted facilities are in the same location of the public listed owner. FOREIGN is for those public listed owners whose impacted facilities are located abroad.

	ALL				HOME				FOREIGN			
	Mkt	3F	4F	5F	Mkt	3F	4F	5F	Mkt	3F	4F	5F
t												
$\text{CAAR}_{t=(-2)}$	0.08	0.07	0.03	0.11	-0.5	-0.59	-0.62	-0.58	0.34	0.36	0.33	0.42
	(-0.12)	(-0.4)	(-0.49)	(-0.09)	(-2.34)	(-2.83)	(-3.05)	(-2.93)	(1.72)	(1.46)	(1.43)	(1.79)
$\text{CAAR}_{t=(-1)}$	0.09	0.04	0.01	0.06	-0.53	-0.64	-0.64	-0.74	0.37	0.34	0.31	0.41
	(-0.5)	(-0.78)	(-0.8)	(-0.58)	(-1.48)	(-1.92)	(-1.95)	(-2.1)	(1.08)	(0.98)	(0.97)	(1.26)
$\text{CAAR}_{t=(0)}$	-0.38	-0.31	-0.27	-0.24	-1.79	-1.93	-1.88	-1.98	0.24	0.41	0.44	0.54
	(-1.71)	(-1.3)	(-1.15)	(-0.92)	(-3.18)	(-3.54)	(-3.48)	(-3.88)	(0.93)	(1.57)	(1.59)	(2.23)
$\text{CAAR}_{t=(1)}$	-0.4	-0.26	-0.18	-0.13	-1.5	-1.53	-1.46	-1.37	0.09	0.31	0.38	0.42
	(-2.07)	(-1.05)	(-0.78)	(-0.38)	(-3.83)	(-3.51)	(-3.37)	(-3.2)	(0.7)	(1.77)	(1.72)	(2.35)
$\text{CAAR}_{t=(2)}$	-0.27	-0.03	-0.02	0.03	-1.17	-1.02	-0.99	-0.99	0.13	0.4	0.41	0.48
	(-2.01)	(-0.91)	(-0.82)	(-0.5)	(-3.92)	(-2.96)	(-2.79)	(-3.11)	(0.37)	(1.09)	(1.08)	(1.47)
$\text{CAAR}_{t=(3)}$	0.1	0.42	0.52	0.54	-0.23	0.06	0.2	0.15	0.24	0.57	0.66	0.72
	(-0.9)	(0.25)	(0.54)	(1.01)	(-1.72)	(-1.05)	(-0.6)	(-0.87)	(0.38)	(1.05)	(1.05)	(1.52)
$\text{CAAR}_{t=(4)}$	-0.1	0.28	0.44	0.38	-1.05	-0.48	-0.3	-0.45	0.33	0.61	0.77	0.74
	(-0.93)	(0.33)	(0.68)	(0.89)	(-3.76)	(-1.6)	(-1.03)	(-1.27)	(0.52)	(1.15)	(1.16)	(1.54)
$\text{CAAR}_{t=(5)}$	-0.43	0.01	0.15	0.09	-1.57	-1.09	-0.94	-1.16	0.08	0.5	0.64	0.64
	(-1.72)	(-0.5)	(-0.18)	(-0.02)	(-4.52)	(-3.32)	(-2.59)	(-2.94)	(0.2)	(0.9)	(0.92)	(1.24)
$\text{CAAR}_{t=(6)}$	-0.82	-0.34	-0.06	-0.25	-1.66	-1.04	-0.76	-1.0	-0.45	-0.03	0.26	0.09
	(-1.97)	(-0.7)	(-0.12)	(-0.16)	(-3.1)	(-2.33)	(-1.68)	(-1.81)	(-0.62)	(0.16)	(0.4)	(0.5)
$\text{CAAR}_{t=(7)}$	-0.89	-0.39	-0.19	-0.23	-2.79	-2.03	-1.87	-1.96	-0.04	0.34	0.56	0.54
	(-2.39)	(-1.0)	(-0.6)	(-0.27)	(-15.57)	(-4.13)	(-3.3)	(-3.09)	(-0.38)	(0.26)	(0.43)	(0.66)
$\text{CAAR}_{t=(8)}$	-1.01	-0.29	-0.14	-0.06	-2.08	-1.07	-0.97	-0.57	-0.53	0.06	0.23	0.17
	(-3.52)	(-1.54)	(-1.16)	(-0.51)	(-14.83)	(-2.29)	(-1.69)	(-0.61)	(-0.95)	(-0.25)	(-0.09)	(0.17)
$\text{CAAR}_{t=(9)}$	-1.44	-0.7	-0.61	-0.42	-3.01	-1.86	-1.81	-1.47	-0.74	-0.18	-0.08	0.05
	(-3.98)	(-2.29)	(-2.07)	(-1.02)	(-5.96)	(-3.57)	(-3.16)	(-2.88)	(-1.11)	(-0.17)	(-0.03)	(0.48)
$\text{CAAR}_{t=(10)}$	-1.42	-0.65	-0.59	-0.42	-3.24	-2.01	-1.97	-1.78	-0.61	-0.05	0.02	0.18
	(-4.05)	(-2.16)	(-1.96)	(-1.12)	(-8.06)	(-5.78)	(-5.35)	(-5.22)	(-1.1)	(-0.17)	(-0.04)	(0.43)
$\text{CAAR}_{t=(11)}$	-1.33	-0.72	-0.71	-0.49	-4.42	-3.48	-3.48	-3.28	0.05	0.5	0.52	0.75
	(-1.91)	(-1.03)	(-1.01)	(-0.41)	(-7.98)	(-6.39)	(-6.33)	(-6.0)	(0.36)	(0.84)	(0.92)	(1.28)
$\text{CAAR}_{t=(12)}$	-1.67	-1.02	-0.91	-0.78	-5.69	-4.62	-4.48	-4.16	0.11	0.58	0.68	0.72
	(-2.16)	(-1.14)	(-0.98)	(-0.54)	(-12.43)	(-9.63)	(-8.95)	(-8.04)	(0.57)	(1.08)	(1.18)	(1.5)
$\text{CAAR}_{t=(13)}$	-1.28	-0.5	-0.34	-0.23	-4.5	-3.29	-3.14	-2.72	0.14	0.74	0.91	0.87
	(-1.79)	(-0.38)	(-0.18)	(0.23)	(-8.36)	(-4.45)	(-3.99)	(-3.83)	(0.57)	(1.12)	(1.2)	(1.48)
$\text{CAAR}_{t=(14)}$	-1.13	-0.28	-0.26	0.03	-3.74	-2.66	-2.66	-2.01	0.03	0.78	0.82	0.93
	(-1.28)	(0.14)	(0.16)	(0.8)	(-5.59)	(-3.3)	(-3.17)	(-2.65)	(0.62)	(1.32)	(1.32)	(1.62)
$\text{CAAR}_{t=(15)}$	-1.18	-0.36	-0.35	-0.12	-3.8	-2.74	-2.68	-2.16	-0.02	0.69	0.69	0.79
	(-1.07)	(0.17)	(0.19)	(0.7)	(-5.41)	(-4.02)	(-3.85)	(-3.43)	(0.77)	(1.32)	(1.28)	(1.55)
$\text{CAAR}_{t=(16)}$	-1.04	-0.14	-0.02	0.09	-4.12	-2.94	-2.77	-2.3	0.33	1.1	1.21	1.16
	(-0.56)	(0.68)	(0.79)	(1.12)	(-6.27)	(-4.26)	(-3.74)	(-3.59)	(1.11)	(1.7)	(1.66)	(1.92)
$\text{CAAR}_{t=(17)}$	-0.51	0.41	0.52	0.69	-3.81	-2.53	-2.41	-1.65	0.95	1.71	1.82	1.73
	(0.07)	(1.39)	(1.47)	(1.92)	(-5.9)	(-3.36)	(-2.92)	(-2.44)	(1.63)	(2.11)	(2.07)	(2.32)
$\text{CAAR}_{t=(18)}$	0.01	1.02	1.24	1.32	-3.24	-1.75	-1.51	-0.82	1.46	2.25	2.47	2.27
	(0.64)	(2.18)	(2.37)	(2.79)	(-4.44)	(-2.26)	(-1.7)	(-1.26)	(1.98)	(2.43)	(2.4)	(2.65)
$\text{CAAR}_{t=(19)}$	0.47	1.61	1.84	1.85	-3.19	-1.32	-1.08	-0.7	2.1	2.91	3.15	2.99
	(0.82)	(2.64)	(2.76)	(3.26)	(-3.6)	(-1.34)	(-0.92)	(-0.77)	(2.17)	(2.68)	(2.62)	(3.1)
$\text{CAAR}_{t=(20)}$	0.71	2.01	2.24	2.27	-2.88	-0.84	-0.62	-0.25	2.3	3.27	3.51	3.38
	(1.04)	(3.04)	(3.09)	(3.68)	(-2.95)	(-0.63)	(-0.35)	(-0.13)	(2.18)	(2.75)	(2.67)	(3.17)
$\text{CAAR}_{t=(21)}$	1.59	3.08	3.25	3.33	-2.89	-0.32	-0.18	0.3	3.58	4.6	4.77	4.68
	(1.81)	(3.81)	(3.78)	(4.23)	(-2.3)	(0.3)	(0.4)	(0.73)	(2.81)	(3.47)	(3.35)	(3.76)
$\text{CAAR}_{t=(22)}$	2.53	4.18	4.34	4.52	-2.68	0.12	0.26	1.02	4.85	5.98	6.16	6.07
	(2.57)	(4.83)	(4.76)	(5.38)	(-2.51)	(0.74)	(0.83)	(1.5)	(3.31)	(4.16)	(4.0)	(4.37)
N	39	39	39	39	21	21	21	21	20	20	20	20

Table VI. Wildfires- CAAR for the 2017 Wildfires season: In Table (VI) we present unweighted average cumulative average abnormal excess abnormal returns (CAAR) in percentage points for the 2017 wildfire season in Spain and Portugal. CAAR are computed using expected returns are from the market model (Mkt) and the factor models ($3F$,$4F$,$5F$). The variance for the test statistic is computed over the cross section of cumulative abnormal returns (CAR) using the variance estimate by (Boehmer et al., 1991). The resulting t_{BMP} statistics are normally distributed and presented in brackets below the CAAR. N is the number of companies in the cross section and t is the day from the event date. Negative values are before and positive after the event date. The cross section of securities i CAAR is derived over several events. Returns over weekends are omitted, as such an event date during the weekend will be on the next trading day in the analysis. The columns under ALL, are all possible events related to the climate hazard independent from the facility location with respects to the headquarters. HOME means that we only compute CAAR for those companies, whose impacted facilities are in the same location of the public listed owner. FOREIGN is for those public listed owners whose impacted facilities are located abroad.

	ALL				HOME				FOREIGN			
	Mkt	3F	4F	5F	Mkt	3F	4F	5F	Mkt	3F	4F	5F
t												
$\text{CAAR}_{t=(-1)}$	0.14	0.02	-0.05	0.05	-0.04	0.13	0.17	0.24	0.2	-0.02	-0.11	-0.0
	(0.8)	(0.6)	(0.47)	(0.67)	(0.21)	(0.54)	(0.59)	(0.8)	(0.72)	(0.49)	(0.34)	(0.57)
$\text{CAAR}_{t=(0)}$	0.54	0.28	0.27	0.48	0.6	0.78	0.78	0.95	0.53	0.14	0.13	0.35
	(1.5)	(1.07)	(1.04)	(1.38)	(3.29)	(1.67)	(1.66)	(2.31)	(1.18)	(0.81)	(0.78)	(1.11)
$\text{CAAR}_{t=(1)}$	-0.1	-0.37	-0.08	-0.25	1.03	1.16	0.91	1.32	-0.43	-0.81	-0.36	-0.7
	(0.58)	(0.24)	(0.69)	(0.33)	(0.41)	(0.66)	(0.32)	(0.66)	(-0.12)	(-0.36)	(0.15)	(-0.21)
$\text{CAAR}_{t=(2)}$	0.3	0.04	0.21	0.19	-0.67	-0.41	-0.53	-0.25	0.57	0.17	0.42	0.32
	(1.17)	(0.8)	(1.07)	(1.03)	(-0.84)	(-0.83)	(-0.9)	(-0.6)	(1.06)	(0.67)	(0.98)	(0.94)
$\text{CAAR}_{t=(3)}$	0.04	-0.39	-0.27	-0.36	-0.13	0.55	0.45	0.69	0.09	-0.66	-0.47	-0.66
	(-0.33)	(-0.41)	(-0.34)	(-0.4)	(-0.08)	(0.69)	(0.65)	(0.85)	(0.07)	(-0.18)	(-0.03)	(-0.16)
$\text{CAAR}_{t=(4)}$	0.15	-0.48	-0.17	-0.41	0.63	1.22	0.97	1.34	0.01	-0.97	-0.5	-0.91
	(-0.26)	(-0.67)	(-0.43)	(-0.59)	(2.33)	(1.18)	(1.12)	(1.37)	(-0.43)	(-0.93)	(-0.59)	(-0.84)
$\text{CAAR}_{t=(5)}$	0.17	-0.31	-0.14	-0.48	0.49	0.79	0.66	0.72	0.08	-0.63	-0.37	-0.82
	(-0.12)	(-0.51)	(-0.33)	(-0.66)	(0.51)	(39.73)	(5.1)	(8.1)	(-0.42)	(-0.86)	(-0.67)	(-0.98)
$\text{CAAR}_{t=(6)}$	-0.42	-0.69	-1.0	-1.21	1.1	1.47	1.72	1.28	-0.85	-1.31	-1.78	-1.92
	(-0.65)	(-0.83)	(-1.01)	(-1.26)	(18.28)	(2.76)	(2.41)	(3.07)	(-1.07)	(-1.45)	(-1.69)	(-1.86)
$\text{CAAR}_{t=(7)}$	-0.05	-0.45	-0.88	-0.97	1.21	1.69	2.0	1.6	-0.41	-1.06	-1.7	-1.7
	(-0.29)	(-0.6)	(-0.91)	(-1.04)	(1.5)	(7.66)	(4.31)	(128.54)	(-0.84)	(-1.36)	(-1.78)	(-1.8)
$\text{CAAR}_{t=(8)}$	-0.06	-0.3	-0.54	-0.86	1.6	1.6	1.75	1.47	-0.54	-0.85	-1.19	-1.52
	(-0.17)	(-0.33)	(-0.53)	(-0.82)	(3.3)	(3.48)	(5.81)	(1.96)	(-0.88)	(-1.18)	(-1.45)	(-1.61)
$\text{CAAR}_{t=(9)}$	-0.49	-0.46	-0.53	-0.97	1.4	1.26	1.29	1.17	-1.03	-0.96	-1.05	-1.58
	(-0.44)	(-0.32)	(-0.37)	(-0.72)	(2.93)	(1.51)	(1.62)	(0.96)	(-1.23)	(-1.13)	(-1.21)	(-1.47)
$\text{CAAR}_{t=(10)}$	-0.69	-0.61	-1.14	-1.17	1.75	1.78	2.2	1.61	-1.38	-1.29	-2.1	-1.97
	(-0.73)	(-0.56)	(-0.91)	(-1.03)	(2.1)	(2.23)	(6.38)	(1.55)	(-1.59)	(-1.52)	(-1.91)	(-1.95)
$\text{CAAR}_{t=(11)}$	-0.5	-0.42	-1.08	-1.02	2.48	2.36	2.85	2.16	-1.36	-1.21	-2.2	-1.93
	(-0.47)	(-0.31)	(-0.72)	(-0.77)	(1.9)	(1.4)	(2.69)	(1.11)	(-1.45)	(-1.38)	(-1.94)	(-1.89)
$\text{CAAR}_{t=(12)}$	-0.44	-0.25	-1.05	-0.88	2.42	2.34	2.93	2.22	-1.26	-0.99	-2.18	-1.76
	(-0.6)	(-0.32)	(-0.8)	(-0.77)	(22.12)	(8.1)	(12.81)	(4.11)	(-1.33)	(-1.17)	(-1.8)	(-1.62)
$\text{CAAR}_{t=(13)}$	-0.42	-0.32	-1.29	-0.96	2.5	2.57	3.29	2.41	-1.25	-1.14	-2.59	-1.92
	(-0.41)	(-0.17)	(-0.78)	(-0.66)	(4.36)	(5.5)	(18.0)	(3.31)	(-1.34)	(-1.29)	(-2.04)	(-1.75)
$\text{CAAR}_{t=(14)}$	-0.84	-0.87	-1.72	-1.61	2.44	2.51	3.12	2.37	-1.78	-1.83	-3.1	-2.75
	(-0.78)	(-0.74)	(-1.09)	(-1.11)	(2.62)	(3.22)	(17.73)	(1.93)	(-1.53)	(-1.58)	(-2.17)	(-1.98)
$\text{CAAR}_{t=(15)}$	-0.4	-0.52	-1.41	-1.54	3.34	3.52	4.18	3.19	-1.47	-1.67	-3.01	-2.89
	(-0.52)	(-0.52)	(-0.87)	(-1.0)	(21.24)	(6.54)	(4.0)	(13.37)	(-1.15)	(-1.23)	(-1.84)	(-1.77)
$\text{CAAR}_{t=(16)}$	-0.98	-1.12	-2.06	-2.19	0.24	0.35	1.04	-0.0	-1.33	-1.53	-2.94	-2.82
	(-1.23)	(-1.34)	(-1.71)	(-1.93)	(0.42)	(0.48)	(0.68)	(0.34)	(-1.17)	(-1.32)	(-2.01)	(-2.01)
$\text{CAAR}_{t=(17)}$	-1.31	-1.46	-1.98	-2.74	-0.64	-0.62	-0.29	-1.17	-1.5	-1.7	-2.46	-3.19
	(-1.34)	(-1.4)	(-1.64)	(-2.04)	(0.1)	(0.13)	(0.26)	(-0.07)	(-1.18)	(-1.24)	(-1.61)	(-1.95)
$\text{CAAR}_{t=(18)}$	-0.98	-1.15	-1.74	-2.78	-0.92	-0.8	-0.36	-1.48	-1.0	-1.25	-2.14	-3.15
	(-1.22)	(-1.26)	(-1.51)	(-2.15)	(-0.06)	(0.05)	(0.23)	(-0.26)	(-1.02)	(-1.06)	(-1.45)	(-2.01)
$\text{CAAR}_{t=(19)}$	-2.2	-2.36	-3.0	-3.99	-1.52	-1.47	-1.01	-2.17	-2.39	-2.62	-3.56	-4.5
	(-1.82)	(-1.85)	(-2.0)	(-2.63)	(-0.42)	(-0.34)	(-0.05)	(-0.74)	(-1.66)	(-1.71)	(-2.04)	(-2.69)
$\text{CAAR}_{t=(20)}$	-2.26	-2.37	-2.81	-3.84	-0.72	-0.87	-0.57	-1.46	-2.7	-2.8	-3.45	-4.52
	(-2.19)	(-2.16)	(-2.27)	(-3.0)	(-0.22)	(-0.46)	(-0.08)	(-1.21)	(-2.28)	(-2.22)	(-2.5)	(-3.35)
$\text{CAAR}_{t=(21)}$	-3.23	-3.31	-3.74	-4.68	-2.04	-2.14	-1.83	-2.69	-3.57	-3.64	-4.28	-5.25
	(-3.55)	(-3.27)	(-3.28)	(-3.94)	(-0.63)	(-0.73)	(-0.47)	(-1.13)	(-3.74)	(-3.39)	(-3.54)	(-4.35)
$\text{CAAR}_{t=(22)}$	-2.86	-2.98	-3.5	-4.39	-1.23	-1.33	-0.95	-1.86	-3.32	-3.46	-4.23	-5.12
	(-3.82)	(-3.38)	(-3.31)	(-4.02)	(-0.62)	(-0.8)	(-0.29)	(-1.61)	(-3.54)	(-3.26)	(-3.4)	(-4.1)
N	9	9	9	9	2	2	2	2	7	7	7	7

Table VII. Floods: CAAR for the July 2021 summer floods: In Table (VII) we present unweighted average cumulative average abnormal excess abnormal returns (CAAR) in percentage points for all the July 2021 summer flood in Belgium, Germany and the Netherlands. CAAR are computed using expected returns are from the market model (Mkt) and the factor models ($3F$,$4F$,$5F$). The variance for the test statistic is computed over the cross section of cumulative abnormal returns (CAR) using the variance estimate by (Boehmer et al., 1991). The resulting t_{BMP} statistics are normally distributed and presented in brackets below the CAAR. N is the number of companies in the cross section and t is the day from the event date. Negative values are before and positive after the event date. The cross section of securities i CAAR is derived over several events. Returns over weekends are omitted, as such an event date during the weekend will be on the next trading day in the analysis. The columns under ALL, are all possible events related to the climate hazard independent from the facility location with respects to the headquarters. HOME means that we only compute CAAR for those companies, whose impacted facilities are in the same location of the public listed owner. FOREIGN is for those public listed owners whose impacted facilities are located abroad.

	ALL				HOME				FOREIGN			
t	Mkt	3F	4F	5F	Mkt	3F	4F	5F	Mkt	3F	4F	5F
$\text{CAAR}_{t=(-4)}$	0.16	0.04	0.27	-0.0	0.21	0.11	0.27	0.13	0.11	-0.02	0.25	-0.08
	(1.79)	(0.61)	(2.79)	(0.11)	(0.73)	(0.18)	(1.06)	(0.35)	(0.48)	(-0.1)	(1.62)	(-0.81)
$\text{CAAR}_{t=(-3)}$	-0.13	-0.27	-0.13	-0.33	0.15	0.08	0.11	0.06	-0.29	-0.45	-0.27	-0.52
	(-0.84)	(-1.75)	(-0.77)	(-2.27)	(0.32)	(-0.02)	(0.23)	(0.04)	(-1.89)	(-2.59)	(-1.56)	(-3.23)
$\text{CAAR}_{t=(-2)}$	-0.09	-0.23	-0.17	-0.34	0.37	0.22	0.31	0.24	-0.31	-0.46	-0.41	-0.62
	(-0.65)	(-1.48)	(-1.19)	(-2.08)	(0.96)	(0.44)	(0.7)	(0.54)	(-1.91)	(-2.53)	(-2.35)	(-3.46)
$\text{CAAR}_{t=(-1)}$	-0.45	-0.64	-0.7	-0.7	-0.2	-0.45	-0.43	-0.24	-0.58	-0.75	-0.84	-0.94
	(-2.57)	(-3.59)	(-3.92)	(-3.75)	(-0.89)	(-1.82)	(-1.68)	(-1.09)	(-2.68)	(-3.38)	(-3.87)	(-4.23)
$\text{CAAR}_{t=(0)}$	-0.85	-0.93	-0.93	-0.99	-0.31	-0.44	-0.35	-0.18	-1.12	-1.19	-1.22	-1.39
	(-4.28)	(-4.61)	(-4.6)	(-4.63)	(-1.49)	(-2.05)	(-1.71)	(-1.18)	(-4.84)	(-4.86)	(-5.18)	(-5.64)
$\text{CAAR}_{t=(1)}$	-0.6	-0.8	-0.6	-0.82	-0.32	-0.53	-0.26	-0.12	-0.74	-0.95	-0.77	-1.16
	(-2.82)	(-3.57)	(-2.76)	(-3.47)	(-1.43)	(-2.0)	(-1.39)	(-0.94)	(-2.98)	(-3.5)	(-2.91)	(-4.17)
$\text{CAAR}_{t=(2)}$	-0.63	-0.96	-0.47	-0.99	-0.38	-0.68	-0.01	-0.26	-0.75	-1.11	-0.7	-1.34
	(-2.79)	(-4.03)	(-2.16)	(-3.98)	(-1.61)	(-2.29)	(-0.95)	(-1.31)	(-2.83)	(-3.81)	(-2.48)	(-4.55)
$\text{CAAR}_{t=(3)}$	-0.42	-0.8	-0.32	-0.87	-0.13	-0.45	0.13	-0.02	-0.56	-1.0	-0.56	-1.29
	(-1.8)	(-3.21)	(-1.5)	(-3.34)	(-0.77)	(-1.45)	(-0.35)	(-0.46)	(-2.31)	(-3.49)	(-2.19)	(-4.33)
$\text{CAAR}_{t=(4)}$	-0.35	-0.69	-0.56	-0.68	0.06	-0.3	-0.0	0.17	-0.55	-0.92	-0.85	-1.11
	(-1.44)	(-2.62)	(-2.25)	(-2.46)	(-0.34)	(-0.96)	(-0.6)	(-0.04)	(-2.1)	(-3.17)	(-2.91)	(-3.73)
$\text{CAAR}_{t=(5)}$	-0.49	-0.72	-0.74	-0.76	-0.1	-0.34	-0.22	0.02	-0.68	-0.93	-1.03	-1.17
	(-2.08)	(-2.85)	(-3.03)	(-2.85)	(-0.67)	(-1.09)	(-1.14)	(-0.27)	(-2.25)	(-3.0)	(-3.12)	(-3.7)
$\text{CAAR}_{t=(6)}$	-0.71	-0.77	-0.86	-0.75	-0.56	-0.6	-0.58	-0.14	-0.8	-0.89	-1.03	-1.08
	(-2.67)	(-2.91)	(-3.3)	(-2.81)	(-1.32)	(-1.36)	(-1.6)	(-0.45)	(-2.5)	(-2.78)	(-3.04)	(-3.35)
$\text{CAAR}_{t=(7)}$	-0.49	-0.59	-0.48	-0.53	-0.23	-0.28	-0.03	0.22	-0.63	-0.78	-0.74	-0.91
	(-1.82)	(-2.14)	(-1.92)	(-1.88)	(-0.59)	(-0.64)	(-0.36)	(0.3)	(-1.82)	(-2.19)	(-2.03)	(-2.51)
$\text{CAAR}_{t=(8)}$	-0.82	-0.91	-0.79	-0.85	-0.32	-0.38	-0.15	0.02	-1.07	-1.21	-1.14	-1.29
	(-2.53)	(-2.76)	(-2.52)	(-2.53)	(-0.7)	(-0.74)	(-0.55)	(-0.04)	(-2.81)	(-2.99)	(-2.78)	(-3.19)
$\text{CAAR}_{t=(9)}$	-0.72	-0.85	-0.54	-0.69	-0.03	-0.13	0.3	0.51	-1.07	-1.25	-1.0	-1.31
	(-2.25)	(-2.59)	(-1.84)	(-2.09)	(-0.2)	(-0.28)	(0.17)	(0.61)	(-2.88)	(-3.13)	(-2.57)	(-3.2)
$\text{CAAR}_{t=(10)}$	-1.12	-1.14	-1.14	-0.99	-0.14	-0.2	0.0	0.4	-1.59	-1.62	-1.73	-1.68
	(-3.2)	(-3.26)	(-3.39)	(-2.73)	(-0.3)	(-0.36)	(-0.35)	(0.44)	(-3.99)	(-3.89)	(-4.1)	(-3.92)
$\text{CAAR}_{t=(11)}$	-1.5	-1.57	-1.4	-1.45	-0.51	-0.61	-0.19	-0.1	-1.96	-2.05	-2.03	-2.11
	(-3.87)	(-3.97)	(-3.73)	(-3.59)	(-0.88)	(-0.99)	(-0.76)	(-0.34)	(-4.49)	(-4.44)	(-4.35)	(-4.49)
$\text{CAAR}_{t=(12)}$	-1.25	-1.5	-1.31	-1.38	0.13	-0.06	0.38	0.43	-1.89	-2.19	-2.14	-2.24
	(-3.27)	(-3.81)	(-3.51)	(-3.46)	(-0.08)	(-0.31)	(-0.11)	(0.26)	(-4.22)	(-4.65)	(-4.48)	(-4.73)
$\text{CAAR}_{t=(13)}$	-0.77	-0.97	-0.8	-0.86	0.72	0.54	1.0	0.9	-1.46	-1.66	-1.67	-1.68
	(-1.99)	(-2.31)	(-2.08)	(-2.07)	(0.56)	(0.41)	(0.6)	(0.77)	(-3.25)	(-3.53)	(-3.45)	(-3.55)
$\text{CAAR}_{t=(14)}$	-1.1	-1.45	-1.1	-1.24	0.86	0.48	1.25	0.98	-1.98	-2.33	-2.21	-2.25
	(-2.65)	(-3.24)	(-2.63)	(-2.84)	(0.7)	(0.29)	(0.82)	(0.81)	(-4.15)	(-4.56)	(-4.29)	(-4.44)
$\text{CAAR}_{t=(15)}$	-0.76	-1.25	-0.66	-1.07	1.23	0.68	1.89	1.25	-1.66	-2.12	-1.87	-2.12
	(-2.19)	(-3.09)	(-2.03)	(-2.73)	(1.16)	(0.52)	(1.47)	(1.11)	(-3.61)	(-4.26)	(-3.79)	(-4.25)
$\text{CAAR}_{t=(16)}$	-0.8	-1.33	-0.91	-1.12	1.31	0.76	1.66	1.32	-1.76	-2.29	-2.15	-2.24
	(-2.29)	(-3.3)	(-2.53)	(-2.9)	(1.34)	(0.64)	(1.37)	(1.2)	(-3.4)	(-4.23)	(-3.96)	(-4.1)
$\text{CAAR}_{t=(17)}$	-0.7	-1.36	-0.91	-1.2	1.38	0.66	1.66	1.13	-1.67	-2.3	-2.15	-2.28
	(-2.14)	(-3.39)	(-2.51)	(-3.05)	(1.49)	(0.54)	(1.41)	(1.01)	(-3.29)	(-4.25)	(-3.99)	(-4.17)
$\text{CAAR}_{t=(18)}$	-0.42	-1.2	-0.66	-1.0	1.96	1.01	2.31	1.58	-1.53	-2.2	-2.08	-2.19
	(-1.48)	(-2.95)	(-1.94)	(-2.58)	(2.31)	(1.13)	(2.15)	(1.66)	(-2.88)	(-3.84)	(-3.59)	(-3.77)
$\text{CAAR}_{t=(19)}$	-0.15	-0.95	-0.41	-0.72	2.41	1.5	2.79	2.1	-1.3	-2.02	-1.9	-1.98
	(-0.86)	(-2.32)	(-1.38)	(-1.93)	(2.67)	(1.65)	(2.52)	(2.21)	(-2.46)	(-3.51)	(-3.23)	(-3.42)
$\text{CAAR}_{t=(20)}$	0.2	-0.63	-0.1	-0.41	3.26	2.18	3.57	2.66	-1.18	-1.85	-1.82	-1.74
	(-0.04)	(-1.39)	(-0.5)	(-1.04)	(3.14)	(2.13)	(2.73)	(2.57)	(-2.04)	(-2.95)	(-2.58)	(-2.75)
$\text{CAAR}_{t=(21)}$	0.2	-0.65	-0.1	-0.48	3.26	2.11	3.6	2.54	-1.12	-1.78	-1.79	-1.73
	(0.12)	(-1.19)	(-0.39)	(-0.94)	(3.19)	(2.09)	(2.75)	(2.47)	(-1.89)	(-2.72)	(-2.5)	(-2.65)
$\text{CAAR}_{t=(22)}$	0.26	-0.53	0.05	-0.43	3.25	2.11	3.76	2.49	-1.02	-1.6	-1.63	-1.63
	(0.55)	(-0.61)	(0.13)	(-0.44)	(3.4)	(2.36)	(2.92)	(2.66)	(-1.62)	(-2.25)	(-2.09)	(-2.24)
N	215	215	215	215	73	73	73	73	147	147	147	147

Table VIII. Winter windstorms- CAAR for all events: In Table (XII) we present unweighted average cumulative average abnormal excess abnormal returns (CAAR) in percentage points for all winter windstorms. CAAR are computed using expected returns are from the market model (Mkt) and the factor models ($3F$,$4F$,$5F$). The variance for the test statistic is computed over the cross section of cumulative abnormal returns (CAR) using the variance estimate by (Boehmer et al., 1991). The resulting t_{BMP} statistics are normally distributed and presented in brackets below the CAAR. N is the number of companies in the cross section and t is the day from the event date. Negative values are before and positive after the event date. The cross section of securities i CAAR is derived over several events. Returns over weekends are omitted, as such an event date during the weekend will be on the next trading day in the analysis. The columns under ALL, are all possible events related to the climate hazard independent from the facility location with respects to the headquarters. HOME means that we only compute CAAR for those companies, whose impacted facilities are in the same location of the public listed owner. FOREIGN is for those public listed owners whose impacted facilities are located abroad.

	ALL				HOME				FOREIGN			
	Mkt	3F	4F	5F	Mkt	3F	4F	5F	Mkt	3F	4F	5F
t												
CAAR$_{t=(-1)}$	0.08	0.12	0.05	0.13	-0.19	-0.13	-0.16	-0.14	0.21	0.25	0.16	0.27
	(0.89)	(1.35)	(0.8)	(1.57)	(-1.66)	(-1.33)	(-1.43)	(-1.44)	(1.53)	(1.91)	(1.21)	(2.19)
CAAR$_{t=(0)}$	0.02	0.11	-0.04	0.11	-0.01	0.05	-0.09	0.04	0.04	0.13	-0.01	0.14
	(0.3)	(0.93)	(-0.14)	(1.1)	(0.21)	(0.55)	(-0.43)	(0.36)	(0.2)	(0.86)	(0.13)	(1.14)
CAAR$_{t=(1)}$	0.16	0.27	0.11	0.25	0.26	0.37	0.24	0.32	0.12	0.23	0.05	0.23
	(1.24)	(2.13)	(1.16)	(1.98)	(1.66)	(2.19)	(1.51)	(1.75)	(0.96)	(1.68)	(1.0)	(1.81)
CAAR$_{t=(2)}$	0.21	0.34	0.09	0.31	0.22	0.34	0.12	0.3	0.22	0.34	0.09	0.33
	(1.07)	(1.82)	(0.44)	(1.73)	(0.91)	(1.41)	(0.56)	(1.08)	(1.23)	(1.9)	(0.86)	(2.05)
CAAR$_{t=(3)}$	0.14	0.34	0.03	0.34	0.25	0.4	0.06	0.36	0.09	0.3	0.02	0.33
	(0.48)	(1.57)	(-0.01)	(1.64)	(1.28)	(1.88)	(0.62)	(1.59)	(0.45)	(1.36)	(0.33)	(1.63)
CAAR$_{t=(4)}$	-0.08	0.13	-0.14	0.15	-0.09	0.05	-0.28	0.02	-0.07	0.18	-0.06	0.23
	(-0.73)	(0.4)	(-0.86)	(0.57)	(-0.66)	(-0.03)	(-1.23)	(-0.12)	(-0.22)	(0.72)	(-0.03)	(1.03)
CAAR$_{t=(5)}$	0.02	0.25	0.0	0.26	-0.07	0.13	-0.17	0.1	0.07	0.32	0.09	0.34
	(-0.15)	(1.0)	(-0.08)	(1.09)	(-0.31)	(0.54)	(-0.38)	(0.52)	(0.38)	(1.26)	(0.56)	(1.41)
CAAR$_{t=(6)}$	0.18	0.43	0.1	0.42	0.2	0.47	0.03	0.46	0.19	0.42	0.17	0.42
	(0.54)	(1.81)	(0.26)	(1.83)	(0.51)	(1.61)	(0.09)	(1.71)	(0.78)	(1.62)	(0.72)	(1.67)
CAAR$_{t=(7)}$	0.11	0.4	0.04	0.38	0.01	0.34	-0.19	0.33	0.18	0.45	0.18	0.42
	(0.35)	(1.65)	(0.12)	(1.65)	(-0.16)	(0.95)	(-0.61)	(1.05)	(0.76)	(1.64)	(0.78)	(1.65)
CAAR$_{t=(8)}$	0.2	0.53	0.18	0.48	-0.04	0.26	-0.19	0.25	0.31	0.64	0.35	0.58
	(0.68)	(2.16)	(0.73)	(2.1)	(-0.31)	(0.73)	(-0.6)	(0.81)	(1.05)	(2.13)	(1.26)	(2.07)
CAAR$_{t=(9)}$	0.23	0.55	0.18	0.5	-0.09	0.27	-0.28	0.27	0.35	0.65	0.39	0.58
	(0.75)	(2.1)	(0.68)	(1.97)	(-0.3)	(0.84)	(-0.78)	(0.9)	(1.18)	(2.02)	(1.28)	(1.91)
CAAR$_{t=(10)}$	0.32	0.69	0.3	0.62	-0.17	0.26	-0.38	0.25	0.53	0.87	0.61	0.77
	(0.98)	(2.54)	(1.01)	(2.28)	(-0.5)	(0.8)	(-0.98)	(0.77)	(1.4)	(2.39)	(1.64)	(2.2)
CAAR$_{t=(11)}$	0.32	0.73	0.35	0.61	-0.14	0.27	-0.34	0.26	0.5	0.9	0.64	0.74
	(0.94)	(2.5)	(1.08)	(1.98)	(-0.12)	(0.92)	(-0.56)	(0.87)	(1.4)	(2.44)	(1.75)	(2.07)
CAAR$_{t=(12)}$	0.43	0.84	0.44	0.71	-0.41	0.06	-0.54	0.08	0.8	1.18	0.9	0.99
	(1.02)	(2.41)	(1.17)	(1.89)	(-0.89)	(0.4)	(-0.93)	(0.4)	(1.62)	(2.43)	(1.83)	(2.02)
CAAR$_{t=(13)}$	0.51	0.95	0.65	0.8	-0.02	0.4	-0.12	0.4	0.74	1.16	0.99	0.95
	(1.21)	(2.68)	(1.68)	(2.11)	(0.28)	(1.22)	(0.08)	(1.2)	(1.47)	(2.38)	(1.92)	(1.92)
CAAR$_{t=(14)}$	0.62	1.08	0.85	0.94	0.43	0.86	0.53	0.88	0.66	1.11	0.95	0.92
	(1.49)	(2.91)	(2.11)	(2.38)	(0.96)	(1.85)	(1.0)	(1.88)	(1.38)	(2.31)	(1.88)	(1.87)
CAAR$_{t=(15)}$	0.58	1.01	0.81	0.87	0.68	1.18	0.85	1.18	0.48	0.85	0.73	0.67
	(1.29)	(2.55)	(1.85)	(2.06)	(1.45)	(2.24)	(1.49)	(2.24)	(0.94)	(1.74)	(1.4)	(1.37)
CAAR$_{t=(16)}$	0.49	0.9	0.71	0.76	0.49	1.03	0.69	1.04	0.42	0.76	0.64	0.57
	(1.01)	(2.17)	(1.52)	(1.75)	(0.98)	(1.91)	(1.11)	(1.95)	(0.72)	(1.44)	(1.09)	(1.08)
CAAR$_{t=(17)}$	0.41	0.85	0.61	0.7	0.54	1.12	0.77	1.12	0.28	0.63	0.44	0.44
	(0.71)	(1.82)	(1.08)	(1.45)	(1.25)	(2.1)	(1.36)	(2.14)	(0.44)	(1.12)	(0.66)	(0.79)
CAAR$_{t=(18)}$	0.38	0.83	0.58	0.68	0.44	1.11	0.71	1.12	0.29	0.63	0.45	0.43
	(0.64)	(1.79)	(1.06)	(1.38)	(1.04)	(2.19)	(1.24)	(2.23)	(0.48)	(1.12)	(0.69)	(0.77)
CAAR$_{t=(19)}$	0.24	0.69	0.48	0.54	0.15	0.78	0.39	0.75	0.23	0.58	0.45	0.4
	(0.34)	(1.44)	(0.86)	(1.06)	(0.3)	(1.53)	(0.54)	(1.42)	(0.32)	(1.0)	(0.68)	(0.72)
CAAR$_{t=(20)}$	0.3	0.79	0.53	0.68	0.3	0.94	0.52	0.93	0.25	0.67	0.46	0.52
	(0.53)	(1.69)	(0.94)	(1.38)	(0.71)	(1.81)	(0.8)	(1.79)	(0.46)	(1.21)	(0.75)	(0.96)
CAAR$_{t=(21)}$	0.56	1.04	0.74	0.97	0.68	1.28	0.74	1.29	0.43	0.85	0.66	0.75
	(1.1)	(2.26)	(1.33)	(2.06)	(1.5)	(2.46)	(1.23)	(2.51)	(0.72)	(1.49)	(0.99)	(1.34)
CAAR$_{t=(22)}$	0.61	1.14	0.74	1.1	0.52	1.16	0.43	1.21	0.58	1.05	0.82	0.98
	(1.33)	(2.55)	(1.41)	(2.47)	(1.09)	(2.21)	(0.63)	(2.3)	(0.94)	(1.76)	(1.21)	(1.68)
N	204	204	204	204	70	70	70	70	136	136	136	136

Table IX. Wildfires: CAAR for all events: In Table (IX) we present unweighted average cumulative average abnormal excess abnormal returns (CAAR) in percentage points for all wildfires. CAAR are computed using expected returns are from the market model (Mkt) and the factor models ($3F$,$4F$,$5F$). The variance for the test statistic is computed over the cross section of cumulative abnormal returns (CAR) using the variance estimate by (Boehmer et al., 1991). The resulting t_{BMP} statistics are normally distributed and presented in brackets below the CAAR. N is the number of companies in the cross section and t is the day from the event date. Negative values are before and positive after the event date. The cross section of securities i CAAR is derived over several events. Returns over weekends are omitted, as such an event date during the weekend will be on the next trading day in the analysis. The columns under ALL, are all possible events related to the climate hazard independent from the facility location with respects to the headquarters. HOME means that we only compute CAAR for those companies, whose impacted facilities are in the same location of the public listed owner. FOREIGN is for those public listed owners whose impacted facilities are located abroad.

	ALL				HOME				FOREIGN			
t	Mkt	3F	4F	5F	Mkt	3F	4F	5F	Mkt	3F	4F	5F
CAAR$_{t=(-2)}$	0.11	0.16	0.09	0.15	0.09	0.14	0.08	0.1	0.16	0.19	0.12	0.2
	(1.59)	(2.71)	(1.23)	(2.4)	(0.65)	(1.62)	(0.73)	(1.18)	(1.69)	(2.53)	(1.17)	(2.78)
CAAR$_{t=(-1)}$	0.07	0.12	0.08	0.11	-0.09	0.06	0.04	-0.02	0.2	0.16	0.1	0.2
	(0.63)	(1.44)	(0.87)	(1.01)	(-1.61)	(-0.12)	(-0.31)	(-0.82)	(1.11)	(1.04)	(0.49)	(1.36)
CAAR$_{t=(0)}$	-0.02	-0.11	-0.09	-0.11	-0.17	-0.15	-0.04	-0.24	0.11	-0.08	-0.15	-0.01
	(-0.18)	(-1.22)	(-1.03)	(-1.39)	(-1.54)	(-1.41)	(-0.91)	(-1.76)	(0.2)	(-1.08)	(-1.55)	(-0.52)
CAAR$_{t=(1)}$	0.07	-0.02	0.0	-0.02	-0.08	-0.12	0.02	-0.21	0.22	0.07	-0.01	0.15
	(0.44)	(-0.54)	(-0.34)	(-0.67)	(-1.24)	(-1.41)	(-0.61)	(-1.96)	(0.79)	(-0.18)	(-0.75)	(0.31)
CAAR$_{t=(2)}$	0.3	0.13	0.15	0.09	-0.09	-0.15	-0.02	-0.29	0.63	0.36	0.29	0.42
	(1.96)	(0.47)	(0.65)	(0.02)	(-1.14)	(-1.35)	(-0.69)	(-2.13)	(2.75)	(1.23)	(0.82)	(1.58)
CAAR$_{t=(3)}$	0.22	0.08	0.08	0.02	-0.11	-0.16	-0.05	-0.33	0.5	0.27	0.18	0.32
	(1.21)	(0.03)	(-0.03)	(-0.62)	(-1.0)	(-1.18)	(-0.75)	(-2.12)	(2.2)	(0.92)	(0.38)	(1.25)
CAAR$_{t=(4)}$	0.1	0.0	-0.09	-0.05	-0.3	-0.29	-0.32	-0.44	0.46	0.27	0.13	0.3
	(0.33)	(-0.33)	(-1.06)	(-0.85)	(-1.52)	(-1.42)	(-1.57)	(-2.19)	(1.59)	(0.74)	(-0.04)	(0.92)
CAAR$_{t=(5)}$	0.14	-0.08	-0.15	-0.16	-0.37	-0.41	-0.45	-0.56	0.59	0.23	0.15	0.23
	(0.46)	(-0.98)	(-1.49)	(-1.53)	(-1.78)	(-1.81)	(-1.96)	(-2.56)	(1.61)	(-0.06)	(-0.47)	(-0.04)
CAAR$_{t=(6)}$	0.23	-0.01	-0.1	-0.1	-0.21	-0.31	-0.35	-0.47	0.63	0.27	0.14	0.25
	(0.99)	(-0.64)	(-1.27)	(-1.2)	(-1.05)	(-1.4)	(-1.54)	(-2.13)	(1.8)	(0.06)	(-0.53)	(-0.05)
CAAR$_{t=(7)}$	0.1	-0.12	-0.25	-0.19	-0.34	-0.39	-0.52	-0.54	0.53	0.17	0.04	0.16
	(0.24)	(-1.12)	(-1.87)	(-1.53)	(-1.21)	(-1.42)	(-1.9)	(-2.16)	(1.24)	(-0.43)	(-0.89)	(-0.41)
CAAR$_{t=(8)}$	0.06	-0.11	-0.22	-0.19	-0.28	-0.34	-0.41	-0.51	0.4	0.15	-0.01	0.13
	(-0.06)	(-1.0)	(-1.64)	(-1.41)	(-0.97)	(-1.21)	(-1.54)	(-1.97)	(0.5)	(-0.57)	(-1.1)	(-0.6)
CAAR$_{t=(9)}$	0.09	-0.09	-0.17	-0.18	-0.2	-0.31	-0.31	-0.47	0.37	0.14	-0.0	0.12
	(0.19)	(-0.83)	(-1.25)	(-1.2)	(-0.69)	(-1.14)	(-1.18)	(-1.83)	(0.59)	(-0.43)	(-0.89)	(-0.5)
CAAR$_{t=(10)}$	0.06	0.02	-0.12	-0.11	-0.24	-0.28	-0.4	-0.45	0.36	0.32	0.16	0.24
	(-0.01)	(-0.34)	(-1.13)	(-0.9)	(-0.75)	(-0.95)	(-1.41)	(-1.71)	(0.56)	(0.31)	(-0.21)	(0.01)
CAAR$_{t=(11)}$	0.24	0.27	0.14	0.15	0.08	0.11	-0.03	-0.06	0.42	0.46	0.34	0.36
	(0.77)	(0.69)	(-0.05)	(0.13)	(0.42)	(0.51)	(0.0)	(-0.1)	(0.64)	(0.58)	(0.22)	(0.17)
CAAR$_{t=(12)}$	0.02	0.15	-0.09	0.03	-0.3	-0.17	-0.5	-0.31	0.33	0.47	0.32	0.36
	(-0.38)	(-0.01)	(-1.15)	(-0.47)	(-0.48)	(-0.18)	(-1.23)	(-0.73)	(0.26)	(0.54)	(0.14)	(0.13)
CAAR$_{t=(13)}$	0.27	0.33	0.05	0.22	-0.06	0.02	-0.36	-0.11	0.6	0.65	0.49	0.57
	(0.59)	(0.69)	(-0.6)	(0.32)	(0.28)	(0.5)	(-0.7)	(0.01)	(0.87)	(0.91)	(0.43)	(0.59)
CAAR$_{t=(14)}$	0.06	0.24	-0.1	0.15	-0.14	0.03	-0.44	-0.11	0.3	0.5	0.3	0.44
	(-0.5)	(0.13)	(-1.41)	(-0.16)	(0.37)	(0.8)	(-0.71)	(0.35)	(-0.28)	(0.26)	(-0.3)	(0.03)
CAAR$_{t=(15)}$	0.36	0.54	0.07	0.46	0.03	0.33	-0.37	0.24	0.69	0.77	0.54	0.69
	(0.9)	(1.52)	(-0.59)	(1.27)	(1.09)	(1.99)	(-0.19)	(1.68)	(1.0)	(1.18)	(0.48)	(0.89)
CAAR$_{t=(16)}$	0.29	0.45	-0.1	0.36	-0.13	0.25	-0.68	0.16	0.75	0.72	0.53	0.63
	(0.45)	(0.95)	(-1.42)	(0.71)	(0.55)	(1.63)	(-0.98)	(1.3)	(1.0)	(0.8)	(0.26)	(0.48)
CAAR$_{t=(17)}$	0.04	0.3	-0.13	0.24	-0.13	0.34	-0.47	0.29	0.27	0.36	0.28	0.27
	(-0.63)	(0.17)	(-1.5)	(0.06)	(0.41)	(1.68)	(-0.52)	(1.44)	(-0.5)	(-0.37)	(-0.56)	(-0.65)
CAAR$_{t=(18)}$	0.07	0.44	-0.07	0.38	-0.1	0.44	-0.45	0.41	0.31	0.55	0.37	0.45
	(-0.6)	(0.54)	(-1.37)	(0.46)	(0.64)	(2.08)	(-0.34)	(1.81)	(-0.33)	(0.15)	(-0.3)	(-0.11)
CAAR$_{t=(19)}$	0.21	0.48	-0.05	0.42	-0.08	0.44	-0.49	0.42	0.53	0.61	0.43	0.48
	(0.02)	(0.74)	(-1.25)	(0.65)	(0.52)	(1.99)	(-0.49)	(1.75)	(0.37)	(0.38)	(-0.13)	(-0.0)
CAAR$_{t=(20)}$	-0.04	0.19	-0.14	0.15	-0.35	0.14	-0.5	0.18	0.34	0.37	0.32	0.23
	(-0.84)	(-0.32)	(-1.54)	(-0.3)	(-0.25)	(1.0)	(-0.61)	(0.93)	(-0.25)	(-0.38)	(-0.51)	(-0.78)
CAAR$_{t=(21)}$	-0.16	0.16	-0.18	0.12	-0.36	0.11	-0.54	0.14	0.11	0.34	0.28	0.2
	(-1.07)	(-0.18)	(-1.37)	(-0.14)	(-0.14)	(1.03)	(-0.47)	(0.92)	(-0.79)	(-0.4)	(-0.53)	(-0.79)
CAAR$_{t=(22)}$	-0.11	0.22	-0.23	0.17	-0.48	0.09	-0.77	0.12	0.3	0.43	0.37	0.29
	(-1.02)	(-0.14)	(-1.58)	(-0.11)	(-0.57)	(0.91)	(-1.12)	(0.8)	(-0.32)	(-0.19)	(-0.31)	(-0.58)
N	625	625	625	625	300	300	300	300	352	352	352	352

Table X. Floods- CAAR for all events: In Table (X) we present unweighted average cumulative average abnormal excess abnormal returns (CAAR) in percentage points for all wildfires. CAAR are computed using expected returns are from the market model (Mkt) and the factor models ($3F$,$4F$,$5F$). The variance for the test statistic is computed over the cross section of cumulative abnormal returns (CAR) using the variance estimate by (Boehmer et al., 1991). The resulting t_{BMP} statistics are normally distributed and presented in brackets below the CAAR. N is the number of companies in the cross section and t is the day from the event date. Negative values are before and positive after the event date. The cross section of securities i CAAR is derived over several events. Returns over weekends are omitted, as such an event date during the weekend will be on the next trading day in the analysis. The columns under ALL, are all possible events related to the climate hazard independent from the facility location with respects to the headquarters. HOME means that we only compute CAAR for those companies, whose impacted facilities are in the same location of the public listed owner. FOREIGN is for those public listed owners whose impacted facilities are located abroad.

	ALL				HOME				FOREIGN			
	Mkt	3F	4F	5F	Mkt	3F	4F	5F	Mkt	3F	4F	5F
t												
$\text{CAAR}_{t=(-4)}$	0.16	0.04	0.27	-0.0	0.21	0.11	0.27	0.13	0.11	-0.02	0.25	-0.08
	(-4.5)	(-4.65)	(-4.66)	(-4.62)	(-3.77)	(-3.93)	(-4.07)	(-3.81)	(-4.73)	(-4.87)	(-4.83)	(-4.88)
$\text{CAAR}_{t=(-3)}$	-0.13	-0.27	-0.13	-0.33	0.15	0.08	0.11	0.06	-0.29	-0.45	-0.27	-0.52
	(-5.22)	(-5.33)	(-5.39)	(-5.29)	(-4.54)	(-4.66)	(-4.84)	(-4.53)	(-5.41)	(-5.52)	(-5.52)	(-5.51)
$\text{CAAR}_{t=(-2)}$	-0.09	-0.23	-0.17	-0.34	0.37	0.22	0.31	0.24	-0.31	-0.46	-0.41	-0.62
	(-5.76)	(-5.88)	(-5.91)	(-5.81)	(-5.15)	(-5.28)	(-5.43)	(-5.14)	(-5.92)	(-6.01)	(-6.0)	(-5.99)
$\text{CAAR}_{t=(-1)}$	-0.45	-0.64	-0.7	-0.7	-0.2	-0.45	-0.43	-0.24	-0.58	-0.75	-0.84	-0.94
	(-6.39)	(-6.49)	(-6.5)	(-6.41)	(-5.81)	(-5.92)	(-6.07)	(-5.8)	(-6.52)	(-6.61)	(-6.56)	(-6.55)
$\text{CAAR}_{t=(0)}$	-0.85	-0.93	-0.93	-0.99	-0.31	-0.44	-0.35	-0.18	-1.12	-1.19	-1.22	-1.39
	(-6.81)	(-6.9)	(-6.89)	(-6.84)	(-6.17)	(-6.24)	(-6.37)	(-6.17)	(-6.96)	(-7.05)	(-6.98)	(-6.98)
$\text{CAAR}_{t=(1)}$	-0.6	-0.8	-0.6	-0.82	-0.32	-0.53	-0.26	-0.12	-0.74	-0.95	-0.77	-1.16
	(-7.22)	(-7.33)	(-7.34)	(-7.28)	(-6.62)	(-6.73)	(-6.87)	(-6.69)	(-7.34)	(-7.45)	(-7.39)	(-7.38)
$\text{CAAR}_{t=(2)}$	-0.63	-0.96	-0.47	-0.99	-0.38	-0.68	-0.01	-0.26	-0.75	-1.11	-0.7	-1.34
	(-7.78)	(-7.86)	(-7.89)	(-7.82)	(-7.12)	(-7.2)	(-7.36)	(-7.21)	(-7.92)	(-7.99)	(-7.97)	(-7.93)
$\text{CAAR}_{t=(3)}$	-0.42	-0.8	-0.32	-0.87	-0.13	-0.45	0.13	-0.02	-0.56	-1.0	-0.56	-1.29
	(-8.22)	(-8.27)	(-8.36)	(-8.23)	(-7.55)	(-7.6)	(-7.87)	(-7.6)	(-8.37)	(-8.4)	(-8.41)	(-8.33)
$\text{CAAR}_{t=(4)}$	-0.35	-0.69	-0.56	-0.68	0.06	-0.3	-0.0	0.17	-0.55	-0.92	-0.85	-1.11
	(-8.69)	(-8.72)	(-8.81)	(-8.68)	(-8.03)	(-8.08)	(-8.31)	(-8.09)	(-8.82)	(-8.83)	(-8.85)	(-8.76)
$\text{CAAR}_{t=(5)}$	-0.49	-0.72	-0.74	-0.76	-0.1	-0.34	-0.22	0.02	-0.68	-0.93	-1.03	-1.17
	(-9.12)	(-9.15)	(-9.18)	(-9.13)	(-8.47)	(-8.5)	(-8.66)	(-8.53)	(-9.24)	(-9.25)	(-9.22)	(-9.2)
$\text{CAAR}_{t=(6)}$	-0.71	-0.77	-0.86	-0.75	-0.56	-0.6	-0.58	-0.14	-0.8	-0.89	-1.03	-1.08
	(-9.44)	(-9.5)	(-9.5)	(-9.47)	(-8.76)	(-8.83)	(-8.93)	(-8.84)	(-9.57)	(-9.6)	(-9.55)	(-9.55)
$\text{CAAR}_{t=(7)}$	-0.49	-0.59	-0.48	-0.53	-0.23	-0.28	-0.03	0.22	-0.63	-0.78	-0.74	-0.91
	(-9.69)	(-9.77)	(-9.76)	(-9.76)	(-8.95)	(-9.06)	(-9.14)	(-9.09)	(-9.84)	(-9.89)	(-9.84)	(-9.85)
$\text{CAAR}_{t=(8)}$	-0.82	-0.91	-0.79	-0.85	-0.32	-0.38	-0.15	0.02	-1.07	-1.21	-1.14	-1.29
	(-10.02)	(-10.1)	(-10.09)	(-10.1)	(-9.29)	(-9.41)	(-9.51)	(-9.46)	(-10.16)	(-10.19)	(-10.15)	(-10.17)
$\text{CAAR}_{t=(9)}$	-0.72	-0.85	-0.54	-0.69	-0.03	-0.13	0.3	0.51	-1.07	-1.25	-1.0	-1.31
	(-10.17)	(-10.25)	(-10.25)	(-10.25)	(-9.5)	(-9.61)	(-9.7)	(-9.62)	(-10.28)	(-10.32)	(-10.29)	(-10.31)
$\text{CAAR}_{t=(10)}$	-1.12	-1.14	-1.14	-0.99	-0.14	-0.2	0.0	0.4	-1.59	-1.62	-1.73	-1.68
	(-10.34)	(-10.41)	(-10.43)	(-10.43)	(-9.71)	(-9.81)	(-9.92)	(-9.87)	(-10.42)	(-10.46)	(-10.43)	(-10.45)
$\text{CAAR}_{t=(11)}$	-1.5	-1.57	-1.4	-1.45	-0.51	-0.61	-0.19	-0.1	-1.96	-2.05	-2.03	-2.11
	(-10.36)	(-10.44)	(-10.43)	(-10.47)	(-9.79)	(-9.9)	(-9.98)	(-9.96)	(-10.42)	(-10.47)	(-10.41)	(-10.46)
$\text{CAAR}_{t=(12)}$	-1.25	-1.5	-1.31	-1.38	0.13	-0.06	0.38	0.43	-1.89	-2.19	-2.14	-2.24
	(-10.36)	(-10.43)	(-10.44)	(-10.44)	(-9.78)	(-9.89)	(-9.98)	(-9.93)	(-10.42)	(-10.45)	(-10.42)	(-10.45)
$\text{CAAR}_{t=(13)}$	-0.77	-0.97	-0.8	-0.86	0.72	0.54	1.0	0.9	-1.46	-1.66	-1.67	-1.68
	(-10.39)	(-10.43)	(-10.43)	(-10.44)	(-9.9)	(-9.98)	(-10.07)	(-10.01)	(-10.42)	(-10.41)	(-10.38)	(-10.41)
$\text{CAAR}_{t=(14)}$	-1.1	-1.45	-1.1	-1.24	0.86	0.48	1.25	0.98	-1.98	-2.33	-2.21	-2.25
	(-10.36)	(-10.42)	(-10.42)	(-10.42)	(-9.89)	(-10.0)	(-10.07)	(-10.0)	(-10.39)	(-10.4)	(-10.37)	(-10.4)
$\text{CAAR}_{t=(15)}$	-0.76	-1.25	-0.66	-1.07	1.23	0.68	1.89	1.25	-1.66	-2.12	-1.87	-2.12
	(-10.12)	(-10.15)	(-10.18)	(-10.18)	(-9.74)	(-9.8)	(-9.92)	(-9.84)	(-10.11)	(-10.11)	(-10.09)	(-10.13)
$\text{CAAR}_{t=(16)}$	-0.8	-1.33	-0.91	-1.12	1.31	0.76	1.66	1.32	-1.76	-2.29	-2.15	-2.24
	(-9.89)	(-9.9)	(-9.94)	(-9.92)	(-9.51)	(-9.55)	(-9.7)	(-9.6)	(-9.88)	(-9.86)	(-9.84)	(-9.86)
$\text{CAAR}_{t=(17)}$	-0.7	-1.36	-0.91	-1.2	1.38	0.66	1.66	1.13	-1.67	-2.3	-2.15	-2.28
	(-9.53)	(-9.52)	(-9.54)	(-9.54)	(-9.18)	(-9.22)	(-9.32)	(-9.26)	(-9.5)	(-9.46)	(-9.45)	(-9.47)
$\text{CAAR}_{t=(18)}$	-0.42	-1.2	-0.66	-1.0	1.96	1.01	2.31	1.58	-1.53	-2.2	-2.08	-2.19
	(-9.03)	(-9.01)	(-9.04)	(-9.02)	(-8.74)	(-8.74)	(-8.85)	(-8.77)	(-9.0)	(-8.95)	(-8.94)	(-8.95)
$\text{CAAR}_{t=(19)}$	-0.15	-0.95	-0.41	-0.72	2.41	1.5	2.79	2.1	-1.3	-2.02	-1.9	-1.98
	(-8.41)	(-8.38)	(-8.4)	(-8.4)	(-8.17)	(-8.17)	(-8.24)	(-8.2)	(-8.36)	(-8.32)	(-8.31)	(-8.32)
$\text{CAAR}_{t=(20)}$	0.2	-0.63	-0.1	-0.41	3.26	2.18	3.57	2.66	-1.18	-1.85	-1.82	-1.74
	(-7.56)	(-7.53)	(-7.55)	(-7.55)	(-7.35)	(-7.35)	(-7.42)	(-7.39)	(-7.51)	(-7.46)	(-7.46)	(-7.47)
$\text{CAAR}_{t=(21)}$	0.2	-0.65	-0.1	-0.48	3.26	2.11	3.6	2.54	-1.12	-1.78	-1.79	-1.73
	(-6.41)	(-6.39)	(-6.4)	(-6.4)	(-6.26)	(-6.25)	(-6.29)	(-6.27)	(-6.35)	(-6.32)	(-6.32)	(-6.33)
$\text{CAAR}_{t=(22)}$	0.26	-0.53	0.05	-0.43	3.25	2.11	3.76	2.49	-1.02	-1.6	-1.63	-1.63
	(-4.68)	(-4.67)	(-4.67)	(-4.68)	(-4.57)	(-4.57)	(-4.59)	(-4.58)	(-4.65)	(-4.63)	(-4.62)	(-4.63)
N	213	213	213	213	73	73	73	73	145	145	145	145

Table XI. CAAR for all Wind Severities (ALL,HOME,FOR) Corrado rank test: In Table (X) we present unweighted average cumulative average abnormal excess abnormal returns (CAAR) in percentage points for all wildfires. CAAR are computed using expected returns are from the market model (Mkt) and the factor models ($3F$,$4F$,$5F$). The variance for the test statistic is computed over the cross section of cumulative abnormal returns (CAR) using the variance estimate by (Boehmer et al., 1991). The resulting t_{BMP} statistics are normally distributed and presented in brackets below the CAAR. N is the number of companies in the cross section and t is the day from the event date. Negative values are before and positive after the event date. The cross section of securities i CAAR is derived over several events. Returns over weekends are omitted, as such an event date during the weekend will be on the next trading day in the analysis. The columns under ALL, are all possible events related to the climate hazard independent from the facility location with respects to the headquarters. HOME means that we only compute CAAR for those companies, whose impacted facilities are in the same location of the public listed owner. FOREIGN is for those public listed owners whose impacted facilities are located abroad.

	ALL				HOME				FOREIGN			
	Mkt	3F	4F	5F	Mkt	3F	4F	5F	Mkt	3F	4F	5F
t												
$\text{CAAR}_{t=(-4)}$	0.16	0.04	0.27	-0.0	0.21	0.11	0.27	0.13	0.11	-0.02	0.25	-0.08
	(1.61)	(0.55)	(2.51)	(0.1)	(0.65)	(0.16)	(0.94)	(0.31)	(0.44)	(-0.09)	(1.47)	(-0.74)
$\text{CAAR}_{t=(-3)}$	-0.13	-0.27	-0.13	-0.33	0.15	0.08	0.11	0.06	-0.29	-0.45	-0.27	-0.52
	(-0.76)	(-1.58)	(-0.69)	(-2.04)	(0.28)	(-0.01)	(0.2)	(0.03)	(-1.72)	(-2.35)	(-1.42)	(-2.93)
$\text{CAAR}_{t=(-2)}$	-0.09	-0.23	-0.17	-0.34	0.37	0.22	0.31	0.24	-0.31	-0.46	-0.41	-0.62
	(-0.58)	(-1.33)	(-1.07)	(-1.87)	(0.85)	(0.39)	(0.62)	(0.48)	(-1.73)	(-2.29)	(-2.14)	(-3.13)
$\text{CAAR}_{t=(-1)}$	-0.45	-0.64	-0.7	-0.7	-0.2	-0.45	-0.43	-0.24	-0.58	-0.75	-0.84	-0.94
	(-2.31)	(-3.23)	(-3.53)	(-3.38)	(-0.79)	(-1.62)	(-1.5)	(-0.97)	(-2.43)	(-3.07)	(-3.51)	(-3.84)
$\text{CAAR}_{t=(0)}$	-0.85	-0.93	-0.93	-0.99	-0.31	-0.44	-0.35	-0.18	-1.12	-1.19	-1.22	-1.39
	(-3.85)	(-4.15)	(-4.14)	(-4.17)	(-1.33)	(-1.82)	(-1.52)	(-1.05)	(-4.39)	(-4.41)	(-4.7)	(-5.12)
$\text{CAAR}_{t=(1)}$	-0.6	-0.8	-0.6	-0.82	-0.32	-0.53	-0.26	-0.12	-0.74	-0.95	-0.77	-1.16
	(-2.54)	(-3.22)	(-2.48)	(-3.13)	(-1.27)	(-1.78)	(-1.23)	(-0.84)	(-2.71)	(-3.18)	(-2.64)	(-3.78)
$\text{CAAR}_{t=(2)}$	-0.63	-0.96	-0.47	-0.99	-0.38	-0.68	-0.01	-0.26	-0.75	-1.11	-0.7	-1.34
	(-2.51)	(-3.62)	(-1.94)	(-3.58)	(-1.43)	(-2.04)	(-0.84)	(-1.17)	(-2.57)	(-3.46)	(-2.25)	(-4.13)
$\text{CAAR}_{t=(3)}$	-0.42	-0.8	-0.32	-0.87	-0.13	-0.45	0.13	-0.02	-0.56	-1.0	-0.56	-1.29
	(-1.62)	(-2.89)	(-1.35)	(-3.01)	(-0.68)	(-1.29)	(-0.31)	(-0.41)	(-2.1)	(-3.16)	(-1.98)	(-3.93)
$\text{CAAR}_{t=(4)}$	-0.35	-0.69	-0.56	-0.68	0.06	-0.3	-0.0	0.17	-0.55	-0.92	-0.85	-1.11
	(-1.29)	(-2.35)	(-2.02)	(-2.21)	(-0.3)	(-0.86)	(-0.53)	(-0.04)	(-1.91)	(-2.88)	(-2.64)	(-3.39)
$\text{CAAR}_{t=(5)}$	-0.49	-0.72	-0.74	-0.76	-0.1	-0.34	-0.22	0.02	-0.68	-0.93	-1.03	-1.17
	(-1.87)	(-2.56)	(-2.72)	(-2.57)	(-0.6)	(-0.97)	(-1.01)	(-0.24)	(-2.04)	(-2.72)	(-2.83)	(-3.35)
$\text{CAAR}_{t=(6)}$	-0.71	-0.77	-0.86	-0.75	-0.56	-0.6	-0.58	-0.14	-0.8	-0.89	-1.03	-1.08
	(-2.4)	(-2.62)	(-2.97)	(-2.52)	(-1.18)	(-1.21)	(-1.42)	(-0.4)	(-2.27)	(-2.52)	(-2.75)	(-3.04)
$\text{CAAR}_{t=(7)}$	-0.49	-0.59	-0.48	-0.53	-0.23	-0.28	-0.03	0.22	-0.63	-0.78	-0.74	-0.91
	(-1.63)	(-1.93)	(-1.73)	(-1.69)	(-0.52)	(-0.57)	(-0.32)	(0.27)	(-1.66)	(-1.98)	(-1.84)	(-2.28)
$\text{CAAR}_{t=(8)}$	-0.82	-0.91	-0.79	-0.85	-0.32	-0.38	-0.15	0.02	-1.07	-1.21	-1.14	-1.29
	(-2.28)	(-2.48)	(-2.26)	(-2.28)	(-0.62)	(-0.66)	(-0.49)	(-0.04)	(-2.55)	(-2.72)	(-2.53)	(-2.89)
$\text{CAAR}_{t=(9)}$	-0.72	-0.85	-0.54	-0.69	-0.03	-0.13	0.3	0.51	-1.07	-1.25	-1.0	-1.31
	(-2.02)	(-2.33)	(-1.66)	(-1.88)	(-0.18)	(-0.25)	(0.15)	(0.54)	(-2.61)	(-2.84)	(-2.33)	(-2.91)
$\text{CAAR}_{t=(10)}$	-1.12	-1.14	-1.14	-0.99	-0.14	-0.2	0.0	0.4	-1.59	-1.62	-1.73	-1.68
	(-2.88)	(-2.93)	(-3.05)	(-2.45)	(-0.27)	(-0.32)	(-0.31)	(0.39)	(-3.62)	(-3.53)	(-3.72)	(-3.56)
$\text{CAAR}_{t=(11)}$	-1.5	-1.57	-1.4	-1.45	-0.51	-0.61	-0.19	-0.1	-1.96	-2.05	-2.03	-2.11
	(-3.48)	(-3.57)	(-3.36)	(-3.23)	(-0.78)	(-0.88)	(-0.68)	(-0.3)	(-4.08)	(-4.03)	(-3.94)	(-4.08)
$\text{CAAR}_{t=(12)}$	-1.25	-1.5	-1.31	-1.38	0.13	-0.06	0.38	0.43	-1.89	-2.19	-2.14	-2.24
	(-2.94)	(-3.43)	(-3.16)	(-3.12)	(-0.07)	(-0.27)	(-0.1)	(0.23)	(-3.83)	(-4.22)	(-4.07)	(-4.29)
$\text{CAAR}_{t=(13)}$	-0.77	-0.97	-0.8	-0.86	0.72	0.54	1.0	0.9	-1.46	-1.66	-1.67	-1.68
	(-1.79)	(-2.08)	(-1.87)	(-1.86)	(0.5)	(0.37)	(0.54)	(0.69)	(-2.94)	(-3.21)	(-3.13)	(-3.22)
$\text{CAAR}_{t=(14)}$	-1.1	-1.45	-1.1	-1.24	0.86	0.48	1.25	0.98	-1.98	-2.33	-2.21	-2.25
	(-2.38)	(-2.92)	(-2.36)	(-2.56)	(0.62)	(0.25)	(0.73)	(0.72)	(-3.77)	(-4.14)	(-3.89)	(-4.02)
$\text{CAAR}_{t=(15)}$	-0.76	-1.25	-0.66	-1.07	1.23	0.68	1.89	1.25	-1.66	-2.12	-1.87	-2.12
	(-1.97)	(-2.78)	(-1.82)	(-2.46)	(1.03)	(0.46)	(1.3)	(0.99)	(-3.28)	(-3.87)	(-3.44)	(-3.85)
$\text{CAAR}_{t=(16)}$	-0.8	-1.33	-0.91	-1.12	1.31	0.76	1.66	1.32	-1.76	-2.29	-2.15	-2.24
	(-2.06)	(-2.97)	(-2.28)	(-2.6)	(1.2)	(0.57)	(1.22)	(1.07)	(-3.08)	(-3.84)	(-3.59)	(-3.72)
$\text{CAAR}_{t=(17)}$	-0.7	-1.36	-0.91	-1.2	1.38	0.66	1.66	1.13	-1.67	-2.3	-2.15	-2.28
	(-1.92)	(-3.05)	(-2.26)	(-2.75)	(1.32)	(0.48)	(1.25)	(0.9)	(-2.98)	(-3.85)	(-3.62)	(-3.78)
$\text{CAAR}_{t=(18)}$	-0.42	-1.2	-0.66	-1.0	1.96	1.01	2.31	1.58	-1.53	-2.2	-2.08	-2.19
	(-1.33)	(-2.65)	(-1.75)	(-2.32)	(2.06)	(1.0)	(1.91)	(1.48)	(-2.61)	(-3.49)	(-3.26)	(-3.42)
$\text{CAAR}_{t=(19)}$	-0.15	-0.95	-0.41	-0.72	2.41	1.5	2.79	2.1	-1.3	-2.02	-1.9	-1.98
	(-0.78)	(-2.08)	(-1.25)	(-1.73)	(2.37)	(1.46)	(2.24)	(1.97)	(-2.23)	(-3.19)	(-2.93)	(-3.1)
$\text{CAAR}_{t=(20)}$	0.2	-0.63	-0.1	-0.41	3.26	2.18	3.57	2.66	-1.18	-1.85	-1.82	-1.74
	(-0.04)	(-1.25)	(-0.45)	(-0.94)	(2.8)	(1.89)	(2.42)	(2.28)	(-1.85)	(-2.68)	(-2.34)	(-2.49)
$\text{CAAR}_{t=(21)}$	0.2	-0.65	-0.1	-0.48	3.26	2.11	3.6	2.54	-1.12	-1.78	-1.79	-1.73
	(0.11)	(-1.07)	(-0.35)	(-0.84)	(2.84)	(1.86)	(2.45)	(2.2)	(-1.71)	(-2.47)	(-2.27)	(-2.4)
$\text{CAAR}_{t=(22)}$	0.26	-0.53	0.05	-0.43	3.25	2.11	3.76	2.49	-1.02	-1.6	-1.63	-1.63
	(0.49)	(-0.55)	(0.12)	(-0.39)	(3.02)	(2.1)	(2.6)	(2.36)	(-1.47)	(-2.04)	(-1.9)	(-2.03)
N	213	213	213	213	73	73	73	73	145	145	145	145

Table XII. CAAR for all Wind Severities (ALL,HOME,FOR) BMP: In Table (X) we present unweighted average cumulative average abnormal excess abnormal returns (CAAR) in percentage points for all wildfires. CAAR are computed using expected returns are from the market model (Mkt) and the factor models ($3F$,$4F$,$5F$). The variance for the test statistic is computed over the cross section of cumulative abnormal returns (CAR) using the variance estimate by (Boehmer et al., 1991). The resulting t_{BMP} statistics are normally distributed and presented in brackets below the CAAR. N is the number of companies in the cross section and t is the day from the event date. Negative values are before and positive after the event date. The cross section of securities i CAAR is derived over several events. Returns over weekends are omitted, as such an event date during the weekend will be on the next trading day in the analysis. The columns under ALL, are all possible events related to the climate hazard independent from the facility location with respects to the headquarters. HOME means that we only compute CAAR for those companies, whose impacted facilities are in the same location of the public listed owner. FOREIGN is for those public listed owners whose impacted facilities are located abroad.

	ALL				HOME				FOREIGN			
t	Mkt	3F	4F	5F	Mkt	3F	4F	5F	Mkt	3F	4F	5F
$\text{CAAR}_{t=(-2)}$	0.11	0.16	0.09	0.15	0.09	0.14	0.08	0.1	0.16	0.19	0.12	0.2
	(1.4)	(2.39)	(1.09)	(2.12)	(0.56)	(1.39)	(0.62)	(1.01)	(1.54)	(2.31)	(1.07)	(2.53)
$\text{CAAR}_{t=(-1)}$	0.07	0.12	0.08	0.11	-0.09	0.06	0.04	-0.02	0.2	0.16	0.1	0.2
	(0.56)	(1.27)	(0.77)	(0.89)	(-1.38)	(-0.11)	(-0.27)	(-0.7)	(1.01)	(0.95)	(0.45)	(1.24)
$\text{CAAR}_{t=(0)}$	-0.02	-0.11	-0.09	-0.11	-0.17	-0.15	-0.04	-0.24	0.11	-0.08	-0.15	-0.01
	(-0.16)	(-1.07)	(-0.91)	(-1.22)	(-1.32)	(-1.21)	(-0.78)	(-1.51)	(0.18)	(-0.98)	(-1.41)	(-0.48)
$\text{CAAR}_{t=(1)}$	0.07	-0.02	0.0	-0.02	-0.08	-0.12	0.02	-0.21	0.22	0.07	-0.01	0.15
	(0.39)	(-0.47)	(-0.3)	(-0.59)	(-1.06)	(-1.21)	(-0.52)	(-1.68)	(0.72)	(-0.17)	(-0.68)	(0.28)
$\text{CAAR}_{t=(2)}$	0.3	0.13	0.15	0.09	-0.09	-0.15	-0.02	-0.29	0.63	0.36	0.29	0.42
	(1.73)	(0.42)	(0.58)	(0.02)	(-0.98)	(-1.15)	(-0.59)	(-1.83)	(2.51)	(1.12)	(0.75)	(1.44)
$\text{CAAR}_{t=(3)}$	0.22	0.08	0.08	0.02	-0.11	-0.16	-0.05	-0.33	0.5	0.27	0.18	0.32
	(1.06)	(0.03)	(-0.02)	(-0.55)	(-0.85)	(-1.01)	(-0.64)	(-1.82)	(2.0)	(0.84)	(0.34)	(1.14)
$\text{CAAR}_{t=(4)}$	0.1	0.0	-0.09	-0.05	-0.3	-0.29	-0.32	-0.44	0.46	0.27	0.13	0.3
	(0.29)	(-0.29)	(-0.93)	(-0.75)	(-1.31)	(-1.21)	(-1.35)	(-1.88)	(1.45)	(0.67)	(-0.04)	(0.84)
$\text{CAAR}_{t=(5)}$	0.14	-0.08	-0.15	-0.16	-0.37	-0.41	-0.45	-0.56	0.59	0.23	0.15	0.23
	(0.41)	(-0.87)	(-1.31)	(-1.35)	(-1.53)	(-1.55)	(-1.68)	(-2.2)	(1.47)	(-0.05)	(-0.43)	(-0.03)
$\text{CAAR}_{t=(6)}$	0.23	-0.01	-0.1	-0.1	-0.21	-0.31	-0.35	-0.47	0.63	0.27	0.14	0.25
	(0.88)	(-0.56)	(-1.12)	(-1.06)	(-0.9)	(-1.2)	(-1.32)	(-1.83)	(1.64)	(0.05)	(-0.48)	(-0.05)
$\text{CAAR}_{t=(7)}$	0.1	-0.12	-0.25	-0.19	-0.34	-0.39	-0.52	-0.54	0.53	0.17	0.04	0.16
	(0.22)	(-0.99)	(-1.65)	(-1.35)	(-1.04)	(-1.22)	(-1.63)	(-1.85)	(1.13)	(-0.39)	(-0.81)	(-0.37)
$\text{CAAR}_{t=(8)}$	0.06	-0.11	-0.22	-0.19	-0.28	-0.34	-0.41	-0.51	0.4	0.15	-0.01	0.13
	(-0.05)	(-0.88)	(-1.45)	(-1.24)	(-0.84)	(-1.03)	(-1.33)	(-1.69)	(0.46)	(-0.52)	(-1.01)	(-0.55)
$\text{CAAR}_{t=(9)}$	0.09	-0.09	-0.17	-0.18	-0.2	-0.31	-0.31	-0.47	0.37	0.14	-0.0	0.12
	(0.17)	(-0.73)	(-1.1)	(-1.06)	(-0.59)	(-0.98)	(-1.01)	(-1.57)	(0.54)	(-0.39)	(-0.81)	(-0.46)
$\text{CAAR}_{t=(10)}$	0.06	0.02	-0.12	-0.11	-0.24	-0.28	-0.4	-0.45	0.36	0.32	0.16	0.24
	(-0.01)	(-0.3)	(-0.99)	(-0.8)	(-0.64)	(-0.82)	(-1.21)	(-1.47)	(0.51)	(0.29)	(-0.19)	(0.01)
$\text{CAAR}_{t=(11)}$	0.24	0.27	0.14	0.15	0.08	0.11	-0.03	-0.06	0.42	0.46	0.34	0.36
	(0.68)	(0.61)	(-0.04)	(0.12)	(0.36)	(0.44)	(0.0)	(-0.09)	(0.59)	(0.53)	(0.2)	(0.15)
$\text{CAAR}_{t=(12)}$	0.02	0.15	-0.09	0.03	-0.3	-0.17	-0.5	-0.31	0.33	0.47	0.32	0.36
	(-0.33)	(-0.01)	(-1.01)	(-0.41)	(-0.41)	(-0.16)	(-1.05)	(-0.62)	(0.24)	(0.49)	(0.12)	(0.12)
$\text{CAAR}_{t=(13)}$	0.27	0.33	0.05	0.22	-0.06	0.02	-0.36	-0.11	0.6	0.65	0.49	0.57
	(0.52)	(0.61)	(-0.53)	(0.28)	(0.24)	(0.43)	(-0.6)	(0.01)	(0.79)	(0.83)	(0.39)	(0.54)
$\text{CAAR}_{t=(14)}$	0.06	0.24	-0.1	0.15	-0.14	0.03	-0.44	-0.11	0.3	0.5	0.3	0.44
	(-0.44)	(0.12)	(-1.24)	(-0.14)	(0.32)	(0.69)	(-0.61)	(0.3)	(-0.26)	(0.24)	(-0.28)	(0.02)
$\text{CAAR}_{t=(15)}$	0.36	0.54	0.07	0.46	0.03	0.33	-0.37	0.24	0.69	0.77	0.54	0.69
	(0.79)	(1.34)	(-0.52)	(1.12)	(0.94)	(1.71)	(-0.16)	(1.44)	(0.91)	(1.08)	(0.44)	(0.81)
$\text{CAAR}_{t=(16)}$	0.29	0.45	-0.1	0.36	-0.13	0.25	-0.68	0.16	0.75	0.72	0.53	0.63
	(0.4)	(0.84)	(-1.26)	(0.62)	(0.47)	(1.4)	(-0.84)	(1.12)	(0.92)	(0.73)	(0.24)	(0.43)
$\text{CAAR}_{t=(17)}$	0.04	0.3	-0.13	0.24	-0.13	0.34	-0.47	0.29	0.27	0.36	0.28	0.27
	(-0.56)	(0.15)	(-1.33)	(0.05)	(0.35)	(1.44)	(-0.44)	(1.23)	(-0.46)	(-0.33)	(-0.51)	(-0.59)
$\text{CAAR}_{t=(18)}$	0.07	0.44	-0.07	0.38	-0.1	0.44	-0.45	0.41	0.31	0.55	0.37	0.45
	(-0.53)	(0.48)	(-1.21)	(0.41)	(0.55)	(1.79)	(-0.29)	(1.55)	(-0.3)	(0.13)	(-0.28)	(-0.1)
$\text{CAAR}_{t=(19)}$	0.21	0.48	-0.05	0.42	-0.08	0.44	-0.49	0.42	0.53	0.61	0.43	0.48
	(0.01)	(0.65)	(-1.1)	(0.58)	(0.45)	(1.71)	(-0.42)	(1.5)	(0.34)	(0.35)	(-0.12)	(-0.0)
$\text{CAAR}_{t=(20)}$	-0.04	0.19	-0.14	0.15	-0.35	0.14	-0.5	0.18	0.34	0.37	0.32	0.23
	(-0.74)	(-0.28)	(-1.35)	(-0.26)	(-0.21)	(0.86)	(-0.52)	(0.79)	(-0.22)	(-0.35)	(-0.47)	(-0.71)
$\text{CAAR}_{t=(21)}$	-0.16	0.16	-0.18	0.12	-0.36	0.11	-0.54	0.14	0.11	0.34	0.28	0.2
	(-0.95)	(-0.16)	(-1.21)	(-0.13)	(-0.12)	(0.89)	(-0.41)	(0.79)	(-0.72)	(-0.36)	(-0.49)	(-0.72)
$\text{CAAR}_{t=(22)}$	-0.11	0.22	-0.23	0.17	-0.48	0.09	-0.77	0.12	0.3	0.43	0.37	0.29
	(-0.9)	(-0.12)	(-1.4)	(-0.1)	(-0.49)	(0.78)	(-0.96)	(0.69)	(-0.29)	(-0.17)	(-0.29)	(-0.53)
N	621	621	621	621	299	299	299	299	350	350	350	350

Table XIII. CAAR for all Flood Severities (ALL,HOME,FOR) BMP: In Table (X) we present unweighted average cumulative average abnormal excess abnormal returns (CAAR) in percentage points for all wildfires. CAAR are computed using expected returns are from the market model (Mkt) and the factor models ($3F$,$4F$,$5F$). The variance for the test statistic is computed over the cross section of cumulative abnormal returns (CAR) using the variance estimate by (Boehmer et al., 1991). The resulting t_{BMP} statistics are normally distributed and presented in brackets below the CAAR. N is the number of companies in the cross section and t is the day from the event date. Negative values are before and positive after the event date. The cross section of securities i CAAR is derived over several events. Returns over weekends are omitted, as such an event date during the weekend will be on the next trading day in the analysis. The columns under ALL, are all possible events related to the climate hazard independent from the facility location with respects to the headquarters. HOME means that we only compute CAAR for those companies, whose impacted facilities are in the same location of the public listed owner. FOREIGN is for those public listed owners whose impacted facilities are located abroad.

t	ALL Mkt	ALL 3F	ALL 4F	ALL 5F	HOME Mkt	HOME 3F	HOME 4F	HOME 5F	FOREIGN Mkt	FOREIGN 3F	FOREIGN 4F	FOREIGN 5F
CAAR$_{t=(-2)}$	0.11	0.16	0.09	0.15	0.09	0.14	0.08	0.1	0.16	0.19	0.12	0.2
	(-4.48)	(-4.45)	(-4.61)	(-4.45)	(-4.43)	(-4.3)	(-4.56)	(-4.29)	(-4.4)	(-4.46)	(-4.52)	(-4.47)
CAAR$_{t=(-1)}$	0.07	0.12	0.08	0.11	-0.09	0.06	0.04	-0.02	0.2	0.16	0.1	0.2
	(-5.27)	(-5.28)	(-5.4)	(-5.27)	(-5.23)	(-5.14)	(-5.36)	(-5.11)	(-5.2)	(-5.29)	(-5.31)	(-5.3)
CAAR$_{t=(0)}$	-0.02	-0.11	-0.09	-0.11	-0.17	-0.15	-0.04	-0.24	0.11	-0.08	-0.15	-0.01
	(-5.97)	(-5.98)	(-6.1)	(-5.96)	(-5.9)	(-5.83)	(-6.06)	(-5.78)	(-5.9)	(-5.97)	(-5.99)	(-5.99)
CAAR$_{t=(1)}$	0.07	-0.02	0.0	-0.02	-0.08	-0.12	0.02	-0.21	0.22	0.07	-0.01	0.15
	(-6.66)	(-6.61)	(-6.75)	(-6.6)	(-6.6)	(-6.5)	(-6.76)	(-6.44)	(-6.56)	(-6.56)	(-6.59)	(-6.6)
CAAR$_{t=(2)}$	0.3	0.13	0.15	0.09	-0.09	-0.15	-0.02	-0.29	0.63	0.36	0.29	0.42
	(-7.35)	(-7.32)	(-7.44)	(-7.3)	(-7.28)	(-7.17)	(-7.42)	(-7.11)	(-7.25)	(-7.29)	(-7.3)	(-7.33)
CAAR$_{t=(3)}$	0.22	0.08	0.08	0.02	-0.11	-0.16	-0.05	-0.33	0.5	0.27	0.18	0.32
	(-8.04)	(-7.99)	(-8.11)	(-7.97)	(-7.89)	(-7.78)	(-8.02)	(-7.71)	(-8.0)	(-8.0)	(-8.02)	(-8.04)
CAAR$_{t=(4)}$	0.1	0.0	-0.09	-0.05	-0.3	-0.29	-0.32	-0.44	0.46	0.27	0.13	0.3
	(-8.58)	(-8.54)	(-8.66)	(-8.51)	(-8.44)	(-8.34)	(-8.56)	(-8.26)	(-8.51)	(-8.53)	(-8.55)	(-8.56)
CAAR$_{t=(5)}$	0.14	-0.08	-0.15	-0.16	-0.37	-0.41	-0.45	-0.56	0.59	0.23	0.15	0.23
	(-9.05)	(-9.04)	(-9.13)	(-9.01)	(-8.92)	(-8.83)	(-9.02)	(-8.77)	(-8.98)	(-9.03)	(-9.04)	(-9.06)
CAAR$_{t=(6)}$	0.23	-0.01	-0.1	-0.1	-0.21	-0.31	-0.35	-0.47	0.63	0.27	0.14	0.25
	(-9.53)	(-9.48)	(-9.58)	(-9.46)	(-9.37)	(-9.28)	(-9.46)	(-9.22)	(-9.47)	(-9.48)	(-9.5)	(-9.49)
CAAR$_{t=(7)}$	0.1	-0.12	-0.25	-0.19	-0.34	-0.39	-0.52	-0.54	0.53	0.17	0.04	0.16
	(-9.98)	(-9.92)	(-10.01)	(-9.89)	(-9.84)	(-9.73)	(-9.9)	(-9.67)	(-9.9)	(-9.9)	(-9.91)	(-9.91)
CAAR$_{t=(8)}$	0.06	-0.11	-0.22	-0.19	-0.28	-0.34	-0.41	-0.51	0.4	0.15	-0.01	0.13
	(-10.32)	(-10.26)	(-10.35)	(-10.24)	(-10.21)	(-10.1)	(-10.24)	(-10.03)	(-10.22)	(-10.23)	(-10.25)	(-10.24)
CAAR$_{t=(9)}$	0.09	-0.09	-0.17	-0.18	-0.2	-0.31	-0.31	-0.47	0.37	0.14	-0.0	0.12
	(-10.61)	(-10.57)	(-10.65)	(-10.54)	(-10.54)	(-10.44)	(-10.58)	(-10.36)	(-10.47)	(-10.51)	(-10.53)	(-10.53)
CAAR$_{t=(10)}$	0.06	0.02	-0.12	-0.11	-0.24	-0.28	-0.4	-0.45	0.36	0.32	0.16	0.24
	(-10.86)	(-10.82)	(-10.91)	(-10.79)	(-10.81)	(-10.69)	(-10.85)	(-10.62)	(-10.71)	(-10.75)	(-10.77)	(-10.76)
CAAR$_{t=(11)}$	0.24	0.27	0.14	0.15	0.08	0.11	-0.03	-0.06	0.42	0.46	0.34	0.36
	(-11.03)	(-11.04)	(-11.11)	(-11.0)	(-10.98)	(-10.89)	(-11.01)	(-10.83)	(-10.88)	(-10.99)	(-11.0)	(-10.98)
CAAR$_{t=(12)}$	0.02	0.15	-0.09	0.03	-0.3	-0.17	-0.5	-0.31	0.33	0.47	0.32	0.36
	(-11.18)	(-11.21)	(-11.27)	(-11.17)	(-11.15)	(-11.09)	(-11.2)	(-11.04)	(-11.0)	(-11.12)	(-11.15)	(-11.11)
CAAR$_{t=(13)}$	0.27	0.33	0.05	0.22	-0.06	0.02	-0.36	-0.11	0.6	0.65	0.49	0.57
	(-11.18)	(-11.21)	(-11.26)	(-11.19)	(-11.13)	(-11.07)	(-11.15)	(-11.04)	(-11.02)	(-11.16)	(-11.18)	(-11.15)
CAAR$_{t=(14)}$	0.06	0.24	-0.1	0.15	-0.14	0.03	-0.44	-0.11	0.3	0.5	0.3	0.44
	(-11.18)	(-11.21)	(-11.25)	(-11.19)	(-11.12)	(-11.07)	(-11.13)	(-11.04)	(-11.03)	(-11.15)	(-11.17)	(-11.16)
CAAR$_{t=(15)}$	0.36	0.54	0.07	0.46	0.03	0.33	-0.37	0.24	0.69	0.77	0.54	0.69
	(-10.97)	(-11.04)	(-11.06)	(-11.03)	(-10.94)	(-10.92)	(-10.95)	(-10.89)	(-10.81)	(-10.97)	(-10.98)	(-10.99)
CAAR$_{t=(16)}$	0.29	0.45	-0.1	0.36	-0.13	0.25	-0.68	0.16	0.75	0.72	0.53	0.63
	(-10.79)	(-10.85)	(-10.85)	(-10.85)	(-10.75)	(-10.75)	(-10.74)	(-10.73)	(-10.64)	(-10.78)	(-10.78)	(-10.78)
CAAR$_{t=(17)}$	0.04	0.3	-0.13	0.24	-0.13	0.34	-0.47	0.29	0.27	0.36	0.28	0.27
	(-10.41)	(-10.46)	(-10.45)	(-10.45)	(-10.36)	(-10.36)	(-10.34)	(-10.34)	(-10.28)	(-10.38)	(-10.4)	(-10.39)
CAAR$_{t=(18)}$	0.07	0.44	-0.07	0.38	-0.1	0.44	-0.45	0.41	0.31	0.55	0.37	0.45
	(-9.86)	(-9.92)	(-9.92)	(-9.92)	(-9.85)	(-9.86)	(-9.83)	(-9.85)	(-9.71)	(-9.83)	(-9.84)	(-9.84)
CAAR$_{t=(19)}$	0.21	0.48	-0.05	0.42	-0.08	0.44	-0.49	0.42	0.53	0.61	0.43	0.48
	(-9.18)	(-9.24)	(-9.23)	(-9.24)	(-9.17)	(-9.18)	(-9.15)	(-9.17)	(-9.04)	(-9.16)	(-9.16)	(-9.16)
CAAR$_{t=(20)}$	-0.04	0.19	-0.14	0.15	-0.35	0.14	-0.5	0.18	0.34	0.37	0.32	0.23
	(-8.28)	(-8.32)	(-8.3)	(-8.31)	(-8.26)	(-8.26)	(-8.23)	(-8.26)	(-8.15)	(-8.24)	(-8.24)	(-8.24)
CAAR$_{t=(21)}$	-0.16	0.16	-0.18	0.12	-0.36	0.11	-0.54	0.14	0.11	0.34	0.28	0.2
	(-6.99)	(-7.02)	(-7.02)	(-7.02)	(-6.98)	(-6.98)	(-6.97)	(-6.98)	(-6.89)	(-6.96)	(-6.96)	(-6.95)
CAAR$_{t=(22)}$	-0.11	0.22	-0.23	0.17	-0.48	0.09	-0.77	0.12	0.3	0.43	0.37	0.29
	(-5.11)	(-5.14)	(-5.14)	(-5.14)	(-5.11)	(-5.11)	(-5.11)	(-5.11)	(-5.03)	(-5.09)	(-5.09)	(-5.09)
N	621	621	621	621	299	299	299	299	350	350	350	350

Table XIV. CAAR for all Flood Severities (ALL,HOME,FOR) corrado rank test: In Table (X) we present unweighted average cumulative average abnormal excess abnormal returns (CAAR) in percentage points for all wildfires. CAAR are computed using expected returns are from the market model (Mkt) and the factor models ($3F$,$4F$,$5F$). The variance for the test statistic is computed over the cross section of cumulative abnormal returns (CAR) using the variance estimate by (Boehmer et al., 1991). The resulting t_{BMP} statistics are normally distributed and presented in brackets below the CAAR. N is the number of companies in the cross section and t is the day from the event date. Negative values are before and positive after the event date. The cross section of securities i CAAR is derived over several events. Returns over weekends are omitted, as such an event date during the weekend will be on the next trading day in the analysis. The columns under ALL, are all possible events related to the climate hazard independent from the facility location with respects to the headquarters. HOME means that we only compute CAAR for those companies, whose impacted facilities are in the same location of the public listed owner. FOREIGN is for those public listed owners whose impacted facilities are located abroad.

	ALL				HOME				FOREIGN			
	Mkt	3F	4F	5F	Mkt	3F	4F	5F	Mkt	3F	4F	5F
t												
$\text{CAAR}_{t=(-1)}$	0.08	0.12	0.05	0.13	-0.19	-0.13	-0.16	-0.14	0.21	0.25	0.16	0.27
	(0.75)	(1.13)	(0.67)	(1.32)	(-1.17)	(-0.94)	(-1.01)	(-1.01)	(1.45)	(1.81)	(1.15)	(2.07)
$\text{CAAR}_{t=(0)}$	0.02	0.11	-0.04	0.11	-0.01	0.05	-0.09	0.04	0.04	0.13	-0.01	0.14
	(0.25)	(0.78)	(-0.12)	(0.92)	(0.15)	(0.39)	(-0.3)	(0.25)	(0.19)	(0.81)	(0.12)	(1.08)
$\text{CAAR}_{t=(1)}$	0.16	0.27	0.11	0.25	0.26	0.37	0.24	0.32	0.12	0.23	0.05	0.23
	(1.04)	(1.78)	(0.98)	(1.66)	(1.17)	(1.55)	(1.06)	(1.23)	(0.91)	(1.59)	(0.94)	(1.71)
$\text{CAAR}_{t=(2)}$	0.21	0.34	0.09	0.31	0.22	0.34	0.12	0.3	0.22	0.34	0.09	0.33
	(0.9)	(1.53)	(0.37)	(1.45)	(0.64)	(1.0)	(0.39)	(0.76)	(1.17)	(1.8)	(0.81)	(1.94)
$\text{CAAR}_{t=(3)}$	0.14	0.34	0.03	0.34	0.25	0.4	0.06	0.36	0.09	0.3	0.02	0.33
	(0.4)	(1.32)	(-0.0)	(1.38)	(0.9)	(1.33)	(0.44)	(1.12)	(0.42)	(1.29)	(0.31)	(1.55)
$\text{CAAR}_{t=(4)}$	-0.08	0.13	-0.14	0.15	-0.09	0.05	-0.28	0.02	-0.07	0.18	-0.06	0.23
	(-0.62)	(0.34)	(-0.73)	(0.48)	(-0.47)	(-0.02)	(-0.87)	(-0.08)	(-0.21)	(0.68)	(-0.03)	(0.98)
$\text{CAAR}_{t=(5)}$	0.02	0.25	0.0	0.26	-0.07	0.13	-0.17	0.1	0.07	0.32	0.09	0.34
	(-0.12)	(0.84)	(-0.07)	(0.92)	(-0.22)	(0.38)	(-0.27)	(0.37)	(0.36)	(1.19)	(0.53)	(1.34)
$\text{CAAR}_{t=(6)}$	0.18	0.43	0.1	0.42	0.2	0.47	0.03	0.46	0.19	0.42	0.17	0.42
	(0.45)	(1.52)	(0.21)	(1.54)	(0.36)	(1.14)	(0.06)	(1.2)	(0.74)	(1.53)	(0.68)	(1.58)
$\text{CAAR}_{t=(7)}$	0.11	0.4	0.04	0.38	0.01	0.34	-0.19	0.33	0.18	0.45	0.18	0.42
	(0.29)	(1.38)	(0.1)	(1.39)	(-0.11)	(0.67)	(-0.43)	(0.74)	(0.72)	(1.56)	(0.74)	(1.56)
$\text{CAAR}_{t=(8)}$	0.2	0.53	0.18	0.48	-0.04	0.26	-0.19	0.25	0.31	0.64	0.35	0.58
	(0.57)	(1.81)	(0.61)	(1.76)	(-0.22)	(0.52)	(-0.42)	(0.57)	(0.99)	(2.02)	(1.19)	(1.96)
$\text{CAAR}_{t=(9)}$	0.23	0.55	0.18	0.5	-0.09	0.27	-0.28	0.27	0.35	0.65	0.39	0.58
	(0.63)	(1.76)	(0.57)	(1.65)	(-0.21)	(0.59)	(-0.55)	(0.64)	(1.12)	(1.92)	(1.21)	(1.81)
$\text{CAAR}_{t=(10)}$	0.32	0.69	0.3	0.62	-0.17	0.26	-0.38	0.25	0.53	0.87	0.61	0.77
	(0.82)	(2.13)	(0.85)	(1.92)	(-0.35)	(0.56)	(-0.69)	(0.54)	(1.33)	(2.26)	(1.55)	(2.09)
$\text{CAAR}_{t=(11)}$	0.32	0.73	0.35	0.61	-0.14	0.27	-0.34	0.26	0.5	0.9	0.64	0.74
	(0.79)	(2.1)	(0.91)	(1.66)	(-0.09)	(0.65)	(-0.39)	(0.61)	(1.33)	(2.31)	(1.65)	(1.96)
$\text{CAAR}_{t=(12)}$	0.43	0.84	0.44	0.71	-0.41	0.06	-0.54	0.08	0.8	1.18	0.9	0.99
	(0.85)	(2.02)	(0.98)	(1.59)	(-0.63)	(0.28)	(-0.65)	(0.28)	(1.53)	(2.3)	(1.73)	(1.92)
$\text{CAAR}_{t=(13)}$	0.51	0.95	0.65	0.8	-0.02	0.4	-0.12	0.4	0.74	1.16	0.99	0.95
	(1.02)	(2.25)	(1.41)	(1.77)	(0.19)	(0.86)	(0.05)	(0.85)	(1.39)	(2.26)	(1.82)	(1.82)
$\text{CAAR}_{t=(14)}$	0.62	1.08	0.85	0.94	0.43	0.86	0.53	0.88	0.66	1.11	0.95	0.92
	(1.25)	(2.44)	(1.77)	(1.99)	(0.67)	(1.3)	(0.71)	(1.32)	(1.3)	(2.19)	(1.78)	(1.77)
$\text{CAAR}_{t=(15)}$	0.58	1.01	0.81	0.87	0.68	1.18	0.85	1.18	0.48	0.85	0.73	0.67
	(1.08)	(2.14)	(1.55)	(1.73)	(1.02)	(1.58)	(1.05)	(1.58)	(0.89)	(1.65)	(1.33)	(1.3)
$\text{CAAR}_{t=(16)}$	0.49	0.9	0.71	0.76	0.49	1.03	0.69	1.04	0.42	0.76	0.64	0.57
	(0.85)	(1.82)	(1.27)	(1.47)	(0.69)	(1.35)	(0.78)	(1.38)	(0.68)	(1.36)	(1.04)	(1.02)
$\text{CAAR}_{t=(17)}$	0.41	0.85	0.61	0.7	0.54	1.12	0.77	1.12	0.28	0.63	0.44	0.44
	(0.6)	(1.53)	(0.9)	(1.22)	(0.88)	(1.48)	(0.96)	(1.51)	(0.41)	(1.06)	(0.63)	(0.75)
$\text{CAAR}_{t=(18)}$	0.38	0.83	0.58	0.68	0.44	1.11	0.71	1.12	0.29	0.63	0.45	0.43
	(0.54)	(1.5)	(0.89)	(1.16)	(0.73)	(1.54)	(0.88)	(1.57)	(0.46)	(1.06)	(0.66)	(0.73)
$\text{CAAR}_{t=(19)}$	0.24	0.69	0.48	0.54	0.15	0.78	0.39	0.75	0.23	0.58	0.45	0.4
	(0.29)	(1.21)	(0.72)	(0.89)	(0.21)	(1.08)	(0.38)	(1.0)	(0.3)	(0.95)	(0.64)	(0.68)
$\text{CAAR}_{t=(20)}$	0.3	0.79	0.53	0.68	0.3	0.94	0.52	0.93	0.25	0.67	0.46	0.52
	(0.44)	(1.42)	(0.79)	(1.16)	(0.5)	(1.28)	(0.56)	(1.26)	(0.44)	(1.15)	(0.71)	(0.91)
$\text{CAAR}_{t=(21)}$	0.56	1.04	0.74	0.97	0.68	1.28	0.74	1.29	0.43	0.85	0.66	0.75
	(0.93)	(1.89)	(1.12)	(1.73)	(1.06)	(1.74)	(0.87)	(1.77)	(0.68)	(1.42)	(0.94)	(1.27)
$\text{CAAR}_{t=(22)}$	0.61	1.14	0.74	1.1	0.52	1.16	0.43	1.21	0.58	1.05	0.82	0.98
	(1.12)	(2.14)	(1.19)	(2.07)	(0.76)	(1.56)	(0.45)	(1.62)	(0.89)	(1.67)	(1.14)	(1.59)
N	201	201	201	201	69	69	69	69	134	134	134	134

Table XV. CAAR for all Fire Severities (ALL,HOME,FOR) BMP: In Table (X) we present unweighted average cumulative average abnormal excess abnormal returns (CAAR) in percentage points for all wildfires. CAAR are computed using expected returns are from the market model (Mkt) and the factor models ($3F$,$4F$,$5F$). The variance for the test statistic is computed over the cross section of cumulative abnormal returns (CAR) using the variance estimate by (Boehmer et al., 1991). The resulting t_{BMP} statistics are normally distributed and presented in brackets below the CAAR. N is the number of companies in the cross section and t is the day from the event date. Negative values are before and positive after the event date. The cross section of securities i CAAR is derived over several events. Returns over weekends are omitted, as such an event date during the weekend will be on the next trading day in the analysis. The columns under ALL, are all possible events related to the climate hazard independent from the facility location with respects to the headquarters. HOME means that we only compute CAAR for those companies, whose impacted facilities are in the same location of the public listed owner. FOREIGN is for those public listed owners whose impacted facilities are located abroad.

	ALL				HOME				FOREIGN			
t	Mkt	3F	4F	5F	Mkt	3F	4F	5F	Mkt	3F	4F	5F
$CAAR_{t=(-1)}$	0.08	0.12	0.05	0.13	-0.19	-0.13	-0.16	-0.14	0.21	0.25	0.16	0.27
	(-4.23)	(-4.09)	(-4.18)	(-4.08)	(-4.09)	(-3.99)	(-4.21)	(-3.9)	(-4.31)	(-4.16)	(-4.17)	(-4.19)
$CAAR_{t=(0)}$	0.02	0.11	-0.04	0.11	-0.01	0.05	-0.09	0.04	0.04	0.13	-0.01	0.14
	(-5.08)	(-4.97)	(-5.03)	(-4.96)	(-4.87)	(-4.79)	(-5.01)	(-4.7)	(-5.2)	(-5.08)	(-5.05)	(-5.12)
$CAAR_{t=(1)}$	0.16	0.27	0.11	0.25	0.26	0.37	0.24	0.32	0.12	0.23	0.05	0.23
	(-5.84)	(-5.76)	(-5.78)	(-5.75)	(-5.63)	(-5.54)	(-5.68)	(-5.44)	(-5.96)	(-5.88)	(-5.83)	(-5.93)
$CAAR_{t=(2)}$	0.21	0.34	0.09	0.31	0.22	0.34	0.12	0.3	0.22	0.34	0.09	0.33
	(-6.62)	(-6.55)	(-6.58)	(-6.54)	(-6.41)	(-6.34)	(-6.49)	(-6.24)	(-6.73)	(-6.66)	(-6.62)	(-6.71)
$CAAR_{t=(3)}$	0.14	0.34	0.03	0.34	0.25	0.4	0.06	0.36	0.09	0.3	0.02	0.33
	(-7.32)	(-7.25)	(-7.26)	(-7.25)	(-7.07)	(-7.01)	(-7.14)	(-6.93)	(-7.44)	(-7.38)	(-7.31)	(-7.42)
$CAAR_{t=(4)}$	-0.08	0.13	-0.14	0.15	-0.09	0.05	-0.28	0.02	-0.07	0.18	-0.06	0.23
	(-7.93)	(-7.89)	(-7.88)	(-7.89)	(-7.72)	(-7.67)	(-7.76)	(-7.59)	(-8.03)	(-7.99)	(-7.92)	(-8.05)
$CAAR_{t=(5)}$	0.02	0.25	0.0	0.26	-0.07	0.13	-0.17	0.1	0.07	0.32	0.09	0.34
	(-8.44)	(-8.41)	(-8.42)	(-8.43)	(-8.21)	(-8.16)	(-8.25)	(-8.09)	(-8.56)	(-8.53)	(-8.48)	(-8.61)
$CAAR_{t=(6)}$	0.18	0.43	0.1	0.42	0.2	0.47	0.03	0.46	0.19	0.42	0.17	0.42
	(-9.04)	(-9.01)	(-9.02)	(-9.03)	(-8.77)	(-8.74)	(-8.83)	(-8.68)	(-9.17)	(-9.14)	(-9.09)	(-9.21)
$CAAR_{t=(7)}$	0.11	0.4	0.04	0.38	0.01	0.34	-0.19	0.33	0.18	0.45	0.18	0.42
	(-9.58)	(-9.55)	(-9.55)	(-9.57)	(-9.28)	(-9.28)	(-9.33)	(-9.23)	(-9.72)	(-9.68)	(-9.64)	(-9.75)
$CAAR_{t=(8)}$	0.2	0.53	0.18	0.48	-0.04	0.26	-0.19	0.25	0.31	0.64	0.35	0.58
	(-10.0)	(-10.0)	(-9.99)	(-10.02)	(-9.63)	(-9.66)	(-9.69)	(-9.62)	(-10.18)	(-10.16)	(-10.11)	(-10.22)
$CAAR_{t=(9)}$	0.23	0.55	0.18	0.5	-0.09	0.27	-0.28	0.27	0.35	0.65	0.39	0.58
	(-10.39)	(-10.4)	(-10.4)	(-10.41)	(-9.96)	(-9.98)	(-10.03)	(-9.94)	(-10.58)	(-10.58)	(-10.54)	(-10.63)
$CAAR_{t=(10)}$	0.32	0.69	0.3	0.62	-0.17	0.26	-0.38	0.25	0.53	0.87	0.61	0.77
	(-10.7)	(-10.7)	(-10.7)	(-10.7)	(-10.23)	(-10.26)	(-10.29)	(-10.22)	(-10.91)	(-10.89)	(-10.87)	(-10.92)
$CAAR_{t=(11)}$	0.32	0.73	0.35	0.61	-0.14	0.27	-0.34	0.26	0.5	0.9	0.64	0.74
	(-10.97)	(-10.99)	(-10.98)	(-10.98)	(-10.42)	(-10.48)	(-10.49)	(-10.43)	(-11.21)	(-11.21)	(-11.18)	(-11.24)
$CAAR_{t=(12)}$	0.43	0.84	0.44	0.71	-0.41	0.06	-0.54	0.08	0.8	1.18	0.9	0.99
	(-11.13)	(-11.15)	(-11.14)	(-11.13)	(-10.56)	(-10.62)	(-10.62)	(-10.57)	(-11.37)	(-11.37)	(-11.35)	(-11.39)
$CAAR_{t=(13)}$	0.51	0.95	0.65	0.8	-0.02	0.4	-0.12	0.4	0.74	1.16	0.99	0.95
	(-11.2)	(-11.22)	(-11.22)	(-11.19)	(-10.57)	(-10.64)	(-10.65)	(-10.6)	(-11.49)	(-11.48)	(-11.45)	(-11.47)
$CAAR_{t=(14)}$	0.62	1.08	0.85	0.94	0.43	0.86	0.53	0.88	0.66	1.11	0.95	0.92
	(-11.21)	(-11.23)	(-11.25)	(-11.2)	(-10.63)	(-10.67)	(-10.7)	(-10.63)	(-11.47)	(-11.47)	(-11.46)	(-11.45)
$CAAR_{t=(15)}$	0.58	1.01	0.81	0.87	0.68	1.18	0.85	1.18	0.48	0.85	0.73	0.67
	(-11.12)	(-11.13)	(-11.16)	(-11.1)	(-10.58)	(-10.62)	(-10.66)	(-10.58)	(-11.34)	(-11.35)	(-11.35)	(-11.33)
$CAAR_{t=(16)}$	0.49	0.9	0.71	0.76	0.49	1.03	0.69	1.04	0.42	0.76	0.64	0.57
	(-10.89)	(-10.9)	(-10.93)	(-10.86)	(-10.41)	(-10.44)	(-10.47)	(-10.41)	(-11.1)	(-11.09)	(-11.09)	(-11.07)
$CAAR_{t=(17)}$	0.41	0.85	0.61	0.7	0.54	1.12	0.77	1.12	0.28	0.63	0.44	0.44
	(-10.55)	(-10.55)	(-10.58)	(-10.52)	(-10.07)	(-10.1)	(-10.12)	(-10.08)	(-10.75)	(-10.74)	(-10.74)	(-10.71)
$CAAR_{t=(18)}$	0.38	0.83	0.58	0.68	0.44	1.11	0.71	1.12	0.29	0.63	0.45	0.43
	(-10.04)	(-10.04)	(-10.06)	(-10.02)	(-9.61)	(-9.65)	(-9.66)	(-9.64)	(-10.21)	(-10.2)	(-10.19)	(-10.19)
$CAAR_{t=(19)}$	0.24	0.69	0.48	0.54	0.15	0.78	0.39	0.75	0.23	0.58	0.45	0.4
	(-9.36)	(-9.37)	(-9.39)	(-9.35)	(-8.96)	(-9.0)	(-9.01)	(-8.99)	(-9.52)	(-9.51)	(-9.51)	(-9.5)
$CAAR_{t=(20)}$	0.3	0.79	0.53	0.68	0.3	0.94	0.52	0.93	0.25	0.67	0.46	0.52
	(-8.43)	(-8.43)	(-8.46)	(-8.42)	(-8.05)	(-8.09)	(-8.09)	(-8.07)	(-8.58)	(-8.57)	(-8.58)	(-8.57)
$CAAR_{t=(21)}$	0.56	1.04	0.74	0.97	0.68	1.28	0.74	1.29	0.43	0.85	0.66	0.75
	(-7.15)	(-7.16)	(-7.17)	(-7.15)	(-6.85)	(-6.87)	(-6.87)	(-6.86)	(-7.28)	(-7.27)	(-7.27)	(-7.28)
$CAAR_{t=(22)}$	0.61	1.14	0.74	1.1	0.52	1.16	0.43	1.21	0.58	1.05	0.82	0.98
	(-5.26)	(-5.26)	(-5.27)	(-5.26)	(-5.04)	(-5.06)	(-5.05)	(-5.05)	(-5.35)	(-5.34)	(-5.35)	(-5.35)
N	201	201	201	201	69	69	69	69	134	134	134	134

Table XVI. CAAR for all Fire Severities (ALL,HOME,FOR) Corrado rank test: In Table (X) we present unweighted average cumulative average abnormal excess abnormal returns (CAAR) in percentage points for all wildfires. CAAR are computed using expected returns are from the market model (Mkt) and the factor models ($3F$,$4F$,$5F$). The variance for the test statistic is computed over the cross section of cumulative abnormal returns (CAR) using the variance estimate by (Boehmer et al., 1991). The resulting t_{BMP} statistics are normally distributed and presented in brackets below the CAAR. N is the number of companies in the cross section and t is the day from the event date. Negative values are before and positive after the event date. The cross section of securities i CAAR is derived over several events. Returns over weekends are omitted, as such an event date during the weekend will be on the next trading day in the analysis. The columns under ALL, are all possible events related to the climate hazard independent from the facility location with respects to the headquarters. HOME means that we only compute CAAR for those companies, whose impacted facilities are in the same location of the public listed owner. FOREIGN is for those public listed owners whose impacted facilities are located abroad.

	ALL				HOME				FOREIGN			
	Mkt	3F	4F	5F	Mkt	3F	4F	5F	Mkt	3F	4F	5F
t												
CAAR$_{t=(-2)}$	0.65	0.58	0.47	0.34	0.31	0.49	0.59	0.5	0.75	0.61	0.43	0.29
	(-3.63)	(-3.83)	(-4.01)	(-4.22)	(-1.94)	(-2.06)	(-2.07)	(-2.16)	(-3.6)	(-3.82)	(-4.02)	(-4.24)
CAAR$_{t=(-1)}$	0.8	0.61	0.43	0.41	0.27	0.63	0.77	0.77	0.95	0.6	0.33	0.31
	(-4.37)	(-4.54)	(-4.69)	(-4.87)	(-2.38)	(-2.58)	(-2.61)	(-2.65)	(-4.32)	(-4.47)	(-4.62)	(-4.83)
CAAR$_{t=(0)}$	1.21	0.89	0.77	0.84	0.91	1.31	1.4	1.5	1.29	0.77	0.59	0.66
	(-4.97)	(-5.11)	(-5.26)	(-5.47)	(-2.77)	(-3.03)	(-3.08)	(-3.13)	(-4.88)	(-4.98)	(-5.12)	(-5.36)
CAAR$_{t=(1)}$	0.56	0.23	0.43	0.12	1.35	1.68	1.53	1.87	0.34	-0.18	0.11	-0.38
	(-5.69)	(-5.82)	(-5.98)	(-6.2)	(-3.3)	(-3.58)	(-3.62)	(-3.69)	(-5.53)	(-5.61)	(-5.77)	(-6.01)
CAAR$_{t=(2)}$	0.97	0.65	0.71	0.56	-0.36	0.11	0.09	0.3	1.35	0.81	0.89	0.64
	(-6.05)	(-6.18)	(-6.42)	(-6.56)	(-3.63)	(-3.9)	(-3.91)	(-4.0)	(-5.83)	(-5.92)	(-6.19)	(-6.3)
CAAR$_{t=(3)}$	0.71	0.24	0.25	0.05	0.18	1.07	1.07	1.25	0.86	0.0	0.02	-0.29
	(-6.55)	(-6.68)	(-6.91)	(-7.06)	(-3.62)	(-3.91)	(-3.97)	(-4.02)	(-6.44)	(-6.53)	(-6.77)	(-6.91)
CAAR$_{t=(4)}$	0.83	0.16	0.37	-0.0	0.95	1.77	1.61	1.91	0.79	-0.3	0.02	-0.55
	(-7.04)	(-7.1)	(-7.31)	(-7.45)	(-4.0)	(-4.29)	(-4.35)	(-4.4)	(-6.88)	(-6.88)	(-7.09)	(-7.23)
CAAR$_{t=(5)}$	0.86	0.32	0.39	-0.08	0.83	1.35	1.32	1.29	0.87	0.03	0.13	-0.48
	(-7.5)	(-7.54)	(-7.77)	(-7.89)	(-4.46)	(-4.74)	(-4.73)	(-4.84)	(-7.25)	(-7.23)	(-7.49)	(-7.58)
CAAR$_{t=(6)}$	0.28	-0.06	-0.48	-0.81	1.45	2.02	2.36	1.84	-0.06	-0.65	-1.29	-1.57
	(-7.84)	(-7.9)	(-8.09)	(-8.17)	(-4.64)	(-4.87)	(-4.88)	(-4.93)	(-7.58)	(-7.61)	(-7.82)	(-7.88)
CAAR$_{t=(7)}$	0.65	0.21	-0.33	-0.56	1.58	2.28	2.67	2.2	0.39	-0.38	-1.19	-1.36
	(-8.05)	(-8.13)	(-8.25)	(-8.32)	(-5.01)	(-5.23)	(-5.29)	(-5.27)	(-7.68)	(-7.74)	(-7.84)	(-7.92)
CAAR$_{t=(8)}$	0.64	0.34	-0.01	-0.47	1.97	2.17	2.41	2.05	0.27	-0.19	-0.7	-1.19
	(-8.38)	(-8.46)	(-8.55)	(-8.63)	(-5.2)	(-5.46)	(-5.52)	(-5.52)	(-8.0)	(-8.05)	(-8.11)	(-8.2)
CAAR$_{t=(9)}$	0.22	0.16	-0.01	-0.59	1.78	1.83	1.95	1.75	-0.22	-0.31	-0.56	-1.26
	(-8.66)	(-8.72)	(-8.87)	(-8.89)	(-5.45)	(-5.56)	(-5.57)	(-5.6)	(-8.23)	(-8.33)	(-8.47)	(-8.47)
CAAR$_{t=(10)}$	0.04	0.03	-0.62	-0.79	2.15	2.37	2.87	2.2	-0.57	-0.64	-1.62	-1.64
	(-8.75)	(-8.84)	(-9.03)	(-9.01)	(-5.54)	(-5.6)	(-5.59)	(-5.64)	(-8.3)	(-8.46)	(-8.66)	(-8.6)
CAAR$_{t=(11)}$	0.22	0.23	-0.56	-0.64	2.89	2.95	3.52	2.75	-0.54	-0.55	-1.72	-1.62
	(-8.86)	(-8.97)	(-9.06)	(-9.11)	(-5.7)	(-5.81)	(-5.86)	(-5.83)	(-8.37)	(-8.53)	(-8.59)	(-8.65)
CAAR$_{t=(12)}$	0.29	0.39	-0.53	-0.49	2.83	2.93	3.6	2.82	-0.44	-0.33	-1.71	-1.44
	(-9.03)	(-9.1)	(-9.17)	(-9.23)	(-5.88)	(-5.93)	(-5.99)	(-5.96)	(-8.51)	(-8.64)	(-8.66)	(-8.75)
CAAR$_{t=(13)}$	0.32	0.35	-0.75	-0.55	2.93	3.18	3.97	3.03	-0.42	-0.46	-2.1	-1.58
	(-9.09)	(-9.16)	(-9.2)	(-9.3)	(-5.92)	(-5.97)	(-6.02)	(-6.0)	(-8.57)	(-8.7)	(-8.69)	(-8.81)
CAAR$_{t=(14)}$	-0.1	-0.19	-1.17	-1.19	2.88	3.15	3.83	3.02	-0.95	-1.14	-2.6	-2.4
	(-9.05)	(-9.11)	(-9.13)	(-9.24)	(-5.89)	(-5.97)	(-6.05)	(-5.99)	(-8.52)	(-8.63)	(-8.59)	(-8.74)
CAAR$_{t=(15)}$	0.35	0.17	-0.84	-1.12	3.79	4.18	4.91	3.85	-0.63	-0.97	-2.49	-2.53
	(-8.9)	(-8.96)	(-9.0)	(-9.08)	(-5.79)	(-5.87)	(-5.92)	(-5.88)	(-8.39)	(-8.49)	(-8.49)	(-8.59)
CAAR$_{t=(16)}$	-0.22	-0.42	-1.49	-1.79	0.7	1.02	1.78	0.66	-0.49	-0.83	-2.42	-2.49
	(-8.79)	(-8.83)	(-8.86)	(-8.9)	(-5.75)	(-5.84)	(-5.89)	(-5.83)	(-8.26)	(-8.34)	(-8.33)	(-8.39)
CAAR$_{t=(17)}$	-0.54	-0.76	-1.39	-2.34	-0.18	0.06	0.47	-0.5	-0.65	-1.0	-1.92	-2.87
	(-8.42)	(-8.43)	(-8.45)	(-8.48)	(-5.44)	(-5.49)	(-5.54)	(-5.49)	(-7.94)	(-8.0)	(-7.97)	(-8.03)
CAAR$_{t=(18)}$	-0.22	-0.44	-1.15	-2.37	-0.45	-0.1	0.41	-0.81	-0.15	-0.54	-1.6	-2.82
	(-7.94)	(-7.94)	(-8.0)	(-7.96)	(-5.09)	(-5.13)	(-5.13)	(-5.11)	(-7.51)	(-7.56)	(-7.6)	(-7.55)
CAAR$_{t=(19)}$	-1.42	-1.65	-2.4	-3.6	-1.04	-0.77	-0.24	-1.5	-1.53	-1.91	-3.02	-4.2
	(-7.42)	(-7.42)	(-7.46)	(-7.4)	(-4.69)	(-4.74)	(-4.75)	(-4.71)	(-7.04)	(-7.08)	(-7.1)	(-7.04)
CAAR$_{t=(20)}$	-1.48	-1.66	-2.2	-3.47	-0.24	-0.16	0.22	-0.76	-1.83	-2.09	-2.9	-4.24
	(-6.56)	(-6.55)	(-6.59)	(-6.54)	(-4.15)	(-4.18)	(-4.2)	(-4.16)	(-6.23)	(-6.26)	(-6.27)	(-6.22)
CAAR$_{t=(21)}$	-2.44	-2.6	-3.12	-4.3	-1.54	-1.41	-1.02	-1.97	-2.7	-2.94	-3.73	-4.96
	(-5.56)	(-5.54)	(-5.59)	(-5.54)	(-3.56)	(-3.56)	(-3.56)	(-3.55)	(-5.26)	(-5.28)	(-5.32)	(-5.26)
CAAR$_{t=(22)}$	-2.06	-2.26	-2.88	-4.0	-0.72	-0.57	-0.12	-1.12	-2.45	-2.74	-3.67	-4.82
	(-4.03)	(-4.02)	(-4.06)	(-4.03)	(-2.56)	(-2.57)	(-2.57)	(-2.56)	(-3.82)	(-3.84)	(-3.87)	(-3.83)
N	9	9	9	9	2	2	2	2	7	7	7	7

Table XVII. CAAR for Floods 2021 (ALL,HOME,FOR) corrado rank test: In Table (X) we present unweighted average cumulative average abnormal excess abnormal returns (CAAR) in percentage points for all wildfires. CAAR are computed using expected returns are from the market model (Mkt) and the factor models ($3F$,$4F$,$5F$). The variance for the test statistic is computed over the cross section of cumulative abnormal returns (CAR) using the variance estimate by (Boehmer et al., 1991). The resulting t_{BMP} statistics are normally distributed and presented in brackets below the CAAR. N is the number of companies in the cross section and t is the day from the event date. Negative values are before and positive after the event date. The cross section of securities i CAAR is derived over several events. Returns over weekends are omitted, as such an event date during the weekend will be on the next trading day in the analysis. The columns under ALL, are all possible events related to the climate hazard independent from the facility location with respects to the headquarters. HOME means that we only compute CAAR for those companies, whose impacted facilities are in the same location of the public listed owner. FOREIGN is for those public listed owners whose impacted facilities are located abroad.

	ALL				HOME				FOREIGN			
t	Mkt	3F	4F	5F	Mkt	3F	4F	5F	Mkt	3F	4F	5F
$\text{CAAR}_{t=(-2)}$	0.65	0.58	0.47	0.34	0.31	0.49	0.59	0.5	0.75	0.61	0.43	0.29
	(1.66)	(1.43)	(1.26)	(1.05)	(0.09)	(0.85)	(1.46)	(0.49)	(1.3)	(1.09)	(0.88)	(0.78)
$\text{CAAR}_{t=(-1)}$	0.8	0.61	0.43	0.41	0.27	0.63	0.77	0.77	0.95	0.6	0.33	0.31
	(1.31)	(1.02)	(0.87)	(0.9)	(0.37)	(2.93)	(2.41)	(7.22)	(1.03)	(0.78)	(0.6)	(0.68)
$\text{CAAR}_{t=(0)}$	1.21	0.89	0.77	0.84	0.91	1.31	1.4	1.5	1.29	0.77	0.59	0.66
	(1.58)	(1.22)	(1.13)	(1.21)	(1.33)	(7.95)	(5.75)	(10.17)	(1.21)	(0.92)	(0.81)	(0.93)
$\text{CAAR}_{t=(1)}$	0.56	0.23	0.43	0.12	1.35	1.68	1.53	1.87	0.34	-0.18	0.11	-0.38
	(1.28)	(0.91)	(1.1)	(0.77)	(0.3)	(0.73)	(0.55)	(0.61)	(0.71)	(0.44)	(0.63)	(0.35)
$\text{CAAR}_{t=(2)}$	0.97	0.65	0.71	0.56	-0.36	0.11	0.09	0.3	1.35	0.81	0.89	0.64
	(1.52)	(1.15)	(1.19)	(1.1)	(-0.49)	(-0.25)	(-0.28)	(-0.16)	(1.25)	(0.89)	(0.93)	(0.89)
$\text{CAAR}_{t=(3)}$	0.71	0.24	0.25	0.05	0.18	1.07	1.07	1.25	0.86	0.0	0.02	-0.29
	(0.68)	(0.35)	(0.36)	(0.2)	(0.07)	(1.31)	(1.31)	(2.19)	(0.93)	(0.46)	(0.47)	(0.34)
$\text{CAAR}_{t=(4)}$	0.83	0.16	0.37	-0.0	0.95	1.77	1.61	1.91	0.79	-0.3	0.02	-0.55
	(1.02)	(0.32)	(0.57)	(0.13)	(1.72)	(2.11)	(2.2)	(3.39)	(0.51)	(-0.0)	(0.25)	(-0.17)
$\text{CAAR}_{t=(5)}$	0.86	0.32	0.39	-0.08	0.83	1.35	1.32	1.29	0.87	0.03	0.13	-0.48
	(1.25)	(0.67)	(0.78)	(0.15)	(0.29)	(2.64)	(2.43)	(1.37)	(0.52)	(0.08)	(0.16)	(-0.35)
$\text{CAAR}_{t=(6)}$	0.28	-0.06	-0.48	-0.81	1.45	2.02	2.36	1.84	-0.06	-0.65	-1.29	-1.57
	(0.35)	(0.25)	(-0.18)	(-0.53)	(1.42)	(13.17)	(5.31)	(7.15)	(-0.37)	(-0.6)	(-0.97)	(-1.36)
$\text{CAAR}_{t=(7)}$	0.65	0.21	-0.33	-0.56	1.58	2.28	2.67	2.2	0.39	-0.38	-1.19	-1.36
	(0.69)	(0.54)	(-0.1)	(-0.4)	(0.78)	(10.49)	(17.36)	(2.77)	(-0.2)	(-0.71)	(-1.27)	(-1.85)
$\text{CAAR}_{t=(8)}$	0.64	0.34	-0.01	-0.47	1.97	2.17	2.41	2.05	0.27	-0.19	-0.7	-1.19
	(0.95)	(0.86)	(0.39)	(-0.12)	(1.3)	(2.24)	(3.54)	(1.19)	(-0.1)	(-0.43)	(-0.86)	(-1.38)
$\text{CAAR}_{t=(9)}$	0.22	0.16	-0.01	-0.59	1.78	1.83	1.95	1.75	-0.22	-0.31	-0.56	-1.26
	(0.57)	(0.65)	(0.46)	(-0.14)	(1.15)	(1.32)	(1.62)	(0.76)	(-0.56)	(-0.55)	(-0.73)	(-1.24)
$\text{CAAR}_{t=(10)}$	0.04	0.03	-0.62	-0.79	2.15	2.37	2.87	2.2	-0.57	-0.64	-1.62	-1.64
	(0.24)	(0.46)	(-0.18)	(-0.37)	(1.11)	(1.76)	(3.98)	(1.06)	(-0.94)	(-0.85)	(-1.32)	(-1.66)
$\text{CAAR}_{t=(11)}$	0.22	0.23	-0.56	-0.64	2.89	2.95	3.52	2.75	-0.54	-0.55	-1.72	-1.62
	(0.39)	(0.58)	(-0.09)	(-0.18)	(1.21)	(1.31)	(2.44)	(0.92)	(-0.86)	(-0.8)	(-1.47)	(-1.87)
$\text{CAAR}_{t=(12)}$	0.29	0.39	-0.53	-0.49	2.83	2.93	3.6	2.82	-0.44	-0.33	-1.71	-1.44
	(0.21)	(0.61)	(-0.2)	(-0.22)	(2.84)	(3.74)	(35.08)	(1.95)	(-0.82)	(-0.63)	(-1.41)	(-1.63)
$\text{CAAR}_{t=(13)}$	0.32	0.35	-0.75	-0.55	2.93	3.18	3.97	3.03	-0.42	-0.46	-2.1	-1.58
	(0.49)	(0.81)	(-0.17)	(-0.05)	(1.9)	(3.28)	(26.89)	(1.82)	(-0.81)	(-0.7)	(-1.57)	(-1.7)
$\text{CAAR}_{t=(14)}$	-0.1	-0.19	-1.17	-1.19	2.88	3.15	3.83	3.02	-0.95	-1.14	-2.6	-2.4
	(-0.09)	(-0.01)	(-0.53)	(-0.6)	(1.46)	(2.43)	(7.32)	(1.34)	(-1.0)	(-1.04)	(-1.66)	(-1.85)
$\text{CAAR}_{t=(15)}$	0.35	0.17	-0.84	-1.12	3.79	4.18	4.91	3.85	-0.63	-0.97	-2.49	-2.53
	(0.12)	(0.13)	(-0.38)	(-0.54)	(5.66)	(30.53)	(6.36)	(6.78)	(-0.61)	(-0.68)	(-1.39)	(-1.57)
$\text{CAAR}_{t=(16)}$	-0.22	-0.42	-1.49	-1.79	0.7	1.02	1.78	0.66	-0.49	-0.83	-2.42	-2.49
	(-0.61)	(-0.7)	(-1.18)	(-1.58)	(0.77)	(0.82)	(0.97)	(0.78)	(-0.62)	(-0.82)	(-1.61)	(-1.97)
$\text{CAAR}_{t=(17)}$	-0.54	-0.76	-1.39	-2.34	-0.18	0.06	0.47	-0.5	-0.65	-1.0	-1.92	-2.87
	(-0.78)	(-0.88)	(-1.16)	(-1.74)	(0.23)	(0.36)	(0.5)	(0.1)	(-0.65)	(-0.77)	(-1.21)	(-1.77)
$\text{CAAR}_{t=(18)}$	-0.22	-0.44	-1.15	-2.37	-0.45	-0.1	0.41	-0.81	-0.15	-0.54	-1.6	-2.82
	(-0.6)	(-0.66)	(-0.99)	(-1.82)	(0.04)	(0.3)	(0.5)	(-0.14)	(-0.45)	(-0.53)	(-1.0)	(-1.78)
$\text{CAAR}_{t=(19)}$	-1.42	-1.65	-2.4	-3.6	-1.04	-0.77	-0.24	-1.5	-1.53	-1.91	-3.02	-4.2
	(-1.24)	(-1.26)	(-1.44)	(-2.14)	(-0.51)	(-0.1)	(0.24)	(-0.89)	(-1.06)	(-1.14)	(-1.49)	(-2.24)
$\text{CAAR}_{t=(20)}$	-1.48	-1.66	-2.2	-3.47	-0.24	-0.16	0.22	-0.76	-1.83	-2.09	-2.9	-4.24
	(-1.4)	(-1.43)	(-1.55)	(-2.32)	(-0.13)	(0.12)	(0.56)	(-3.8)	(-1.45)	(-1.54)	(-1.82)	(-2.77)
$\text{CAAR}_{t=(21)}$	-2.44	-2.6	-3.12	-4.3	-1.54	-1.41	-1.02	-1.97	-2.7	-2.94	-3.73	-4.96
	(-2.71)	(-2.46)	(-2.42)	(-3.1)	(-0.82)	(-0.53)	(-0.18)	(-1.5)	(-2.58)	(-2.53)	(-2.6)	(-3.38)
$\text{CAAR}_{t=(22)}$	-2.06	-2.26	-2.88	-4.0	-0.72	-0.57	-0.12	-1.12	-2.45	-2.74	-3.67	-4.82
	(-2.56)	(-2.31)	(-2.25)	(-2.93)	(-1.09)	(-0.39)	(0.24)	(-5.7)	(-2.16)	(-2.19)	(-2.35)	(-3.0)
N	9	9	9	9	2	2	2	2	7	7	7	7

Table XVIII. CAAR for Floods 2021 (ALL,HOME,FOR) BMP: In Table (X) we present unweighted average cumulative average abnormal excess abnormal returns (CAAR) in percentage points for all wildfires. CAAR are computed using expected returns are from the market model (Mkt) and the factor models ($3F$,$4F$,$5F$). The variance for the test statistic is computed over the cross section of cumulative abnormal returns (CAR) using the variance estimate by (Boehmer et al., 1991). The resulting t_{BMP} statistics are normally distributed and presented in brackets below the CAAR. N is the number of companies in the cross section and t is the day from the event date. Negative values are before and positive after the event date. The cross section of securities i CAAR is derived over several events. Returns over weekends are omitted, as such an event date during the weekend will be on the next trading day in the analysis. The columns under ALL, are all possible events related to the climate hazard independent from the facility location with respects to the headquarters. HOME means that we only compute CAAR for those companies, whose impacted facilities are in the same location of the public listed owner. FOREIGN is for those public listed owners whose impacted facilities are located abroad.

	ALL				HOME				FOREIGN			
t	Mkt	3F	4F	5F	Mkt	3F	4F	5F	Mkt	3F	4F	5F
$\text{CAAR}_{t=(-5)}$	-0.09	-0.16	-0.13	-0.1	-0.19	-0.18	-0.22	-0.1	0.0	-0.09	-0.01	-0.04
	(-0.37)	(-0.62)	(-0.33)	(-0.59)	(-0.49)	(-0.59)	(-0.48)	(-0.43)	(0.29)	(0.03)	(0.64)	(-0.04)
$\text{CAAR}_{t=(-4)}$	-0.44	-0.55	-0.51	-0.41	-0.36	-0.36	-0.4	-0.26	-0.48	-0.61	-0.51	-0.44
	(-1.49)	(-1.83)	(-1.58)	(-1.87)	(-0.84)	(-0.95)	(-0.91)	(-0.84)	(-1.3)	(-1.75)	(-1.27)	(-1.27)
$\text{CAAR}_{t=(-3)}$	-1.16	-1.21	-1.19	-1.06	-0.75	-0.71	-0.74	-0.64	-1.52	-1.58	-1.52	-1.35
	(-2.62)	(-2.66)	(-2.71)	(-2.65)	(-1.17)	(-1.23)	(-1.24)	(-1.15)	(-2.41)	(-2.47)	(-2.57)	(-2.05)
$\text{CAAR}_{t=(-2)}$	-1.05	-1.05	-1.04	-1.02	-0.63	-0.56	-0.57	-0.31	-1.46	-1.43	-1.41	-1.63
	(-2.26)	(-2.35)	(-2.37)	(-2.27)	(-1.11)	(-1.19)	(-1.21)	(-0.86)	(-1.7)	(-1.67)	(-1.66)	(-1.77)
$\text{CAAR}_{t=(-1)}$	-1.31	-1.27	-1.27	-1.32	-0.71	-0.61	-0.62	-0.27	-1.96	-1.87	-1.85	-2.33
	(-2.07)	(-2.21)	(-2.21)	(-2.19)	(-1.14)	(-1.34)	(-1.37)	(-0.81)	(-1.93)	(-1.78)	(-1.78)	(-2.06)
$\text{CAAR}_{t=(0)}$	-1.64	-1.67	-1.63	-1.73	-1.1	-1.03	-1.07	-0.61	-2.23	-2.24	-2.14	-2.82
	(-2.27)	(-2.44)	(-2.39)	(-2.39)	(-1.69)	(-1.91)	(-2.02)	(-1.25)	(-2.16)	(-2.06)	(-1.95)	(-2.33)
$\text{CAAR}_{t=(1)}$	-2.14	-2.09	-2.08	-2.19	-1.7	-1.62	-1.64	-1.12	-2.58	-2.49	-2.46	-3.24
	(-2.61)	(-2.7)	(-2.69)	(-2.56)	(-1.98)	(-2.14)	(-2.18)	(-1.52)	(-2.14)	(-2.05)	(-2.01)	(-2.35)
$\text{CAAR}_{t=(2)}$	-2.6	-2.42	-2.45	-2.53	-1.97	-1.86	-1.83	-1.46	-3.2	-2.94	-3.0	-3.59
	(-3.2)	(-3.13)	(-3.12)	(-3.0)	(-2.08)	(-2.21)	(-2.15)	(-1.71)	(-2.97)	(-2.67)	(-2.69)	(-2.89)
$\text{CAAR}_{t=(3)}$	-2.76	-2.54	-2.57	-2.71	-2.06	-1.93	-1.9	-1.47	-3.51	-3.18	-3.26	-4.02
	(-3.56)	(-3.35)	(-3.34)	(-3.15)	(-2.44)	(-2.52)	(-2.42)	(-1.77)	(-3.53)	(-2.93)	(-2.92)	(-3.27)
$\text{CAAR}_{t=(4)}$	-3.22	-2.93	-2.98	-3.0	-2.49	-2.34	-2.29	-1.84	-4.02	-3.59	-3.71	-4.28
	(-3.93)	(-3.54)	(-3.54)	(-3.24)	(-2.8)	(-2.72)	(-2.63)	(-1.96)	(-4.54)	(-3.68)	(-3.56)	(-3.69)
$\text{CAAR}_{t=(5)}$	-3.16	-2.83	-2.89	-2.94	-2.52	-2.36	-2.3	-1.84	-3.85	-3.37	-3.51	-4.16
	(-3.96)	(-3.47)	(-3.51)	(-3.21)	(-3.04)	(-2.8)	(-2.74)	(-2.0)	(-4.26)	(-3.22)	(-3.21)	(-3.46)
$\text{CAAR}_{t=(6)}$	-3.05	-2.8	-2.82	-2.9	-2.88	-2.73	-2.72	-2.24	-3.36	-2.99	-3.03	-3.74
	(-3.63)	(-3.3)	(-3.34)	(-3.11)	(-2.98)	(-2.8)	(-2.81)	(-2.09)	(-3.75)	(-2.83)	(-2.88)	(-3.33)
$\text{CAAR}_{t=(7)}$	-2.7	-2.61	-2.56	-2.64	-2.53	-2.43	-2.47	-1.95	-3.08	-2.93	-2.83	-3.51
	(-3.07)	(-3.0)	(-2.9)	(-2.84)	(-2.55)	(-2.5)	(-2.44)	(-1.88)	(-2.9)	(-2.6)	(-2.37)	(-2.85)
$\text{CAAR}_{t=(8)}$	-3.99	-3.78	-3.76	-3.71	-3.09	-2.96	-2.97	-2.55	-5.02	-4.71	-4.68	-5.0
	(-3.85)	(-3.6)	(-3.59)	(-3.28)	(-2.82)	(-2.74)	(-2.74)	(-2.2)	(-3.12)	(-2.67)	(-2.69)	(-2.66)
$\text{CAAR}_{t=(9)}$	-3.49	-3.29	-3.27	-3.24	-2.72	-2.6	-2.62	-2.11	-4.4	-4.11	-4.05	-4.53
	(-3.01)	(-2.87)	(-2.84)	(-2.53)	(-2.01)	(-1.95)	(-1.93)	(-1.41)	(-2.75)	(-2.37)	(-2.4)	(-2.39)
$\text{CAAR}_{t=(10)}$	-3.23	-3.01	-2.96	-3.04	-2.0	-1.82	-1.87	-1.32	-4.64	-4.28	-4.17	-4.89
	(-2.32)	(-2.25)	(-2.17)	(-2.03)	(-1.34)	(-1.36)	(-1.31)	(-0.93)	(-2.9)	(-2.33)	(-2.37)	(-2.46)
$\text{CAAR}_{t=(11)}$	-3.74	-3.54	-3.46	-3.61	-2.15	-1.98	-2.06	-1.59	-5.42	-5.1	-4.93	-5.68
	(-2.44)	(-2.44)	(-2.33)	(-2.31)	(-1.36)	(-1.48)	(-1.48)	(-1.18)	(-3.23)	(-2.7)	(-2.78)	(-2.84)
$\text{CAAR}_{t=(12)}$	-3.66	-3.42	-3.36	-3.51	-1.77	-1.56	-1.64	-1.24	-5.65	-5.27	-5.11	-5.8
	(-2.33)	(-2.35)	(-2.25)	(-2.25)	(-1.2)	(-1.35)	(-1.36)	(-1.12)	(-3.38)	(-2.68)	(-2.73)	(-2.83)
$\text{CAAR}_{t=(13)}$	-3.0	-2.79	-2.68	-2.78	-1.11	-0.89	-1.0	-0.68	-5.01	-4.66	-4.41	-4.87
	(-1.84)	(-1.89)	(-1.68)	(-1.79)	(-0.83)	(-0.98)	(-0.93)	(-0.83)	(-3.27)	(-2.55)	(-2.6)	(-2.62)
$\text{CAAR}_{t=(14)}$	-2.43	-2.23	-2.1	-2.11	0.47	0.7	0.56	0.75	-5.43	-5.08	-4.78	-4.91
	(-1.24)	(-1.21)	(-0.97)	(-1.14)	(-0.19)	(-0.23)	(-0.16)	(-0.18)	(-3.02)	(-2.41)	(-2.52)	(-2.35)
$\text{CAAR}_{t=(15)}$	-1.2	-1.24	-1.02	-1.18	0.88	1.04	0.82	1.21	-3.37	-3.36	-2.86	-3.44
	(-0.78)	(-0.93)	(-0.5)	(-0.89)	(-0.01)	(-0.11)	(0.03)	(0.01)	(-2.23)	(-1.92)	(-1.91)	(-1.95)
$\text{CAAR}_{t=(16)}$	-2.09	-2.4	-2.09	-2.27	-0.01	0.02	-0.31	0.2	-4.37	-4.75	-4.02	-4.67
	(-1.4)	(-1.71)	(-1.09)	(-1.62)	(-0.49)	(-0.72)	(-0.5)	(-0.57)	(-2.39)	(-2.41)	(-2.48)	(-2.36)
$\text{CAAR}_{t=(17)}$	-1.62	-2.0	-1.67	-1.9	-0.53	-0.47	-0.82	-0.23	-3.08	-3.54	-2.76	-3.6
	(-1.14)	(-1.55)	(-0.84)	(-1.45)	(-0.71)	(-1.07)	(-0.72)	(-0.85)	(-1.94)	(-1.94)	(-1.74)	(-1.94)
$\text{CAAR}_{t=(18)}$	-0.92	-1.45	-1.05	-1.44	0.29	0.32	-0.1	0.69	-2.53	-3.18	-2.25	-3.55
	(-0.61)	(-1.11)	(-0.28)	(-1.05)	(-0.19)	(-0.57)	(-0.17)	(-0.27)	(-1.64)	(-1.71)	(-1.19)	(-1.84)
$\text{CAAR}_{t=(19)}$	0.14	-0.39	0.03	-0.28	1.83	1.87	1.42	2.15	-1.79	-2.45	-1.45	-2.53
	(0.08)	(-0.35)	(0.33)	(-0.31)	(0.51)	(0.33)	(0.45)	(0.51)	(-1.15)	(-1.22)	(-0.6)	(-1.28)
$\text{CAAR}_{t=(20)}$	0.95	-0.23	0.47	-0.09	3.65	3.49	2.74	3.66	-1.86	-3.42	-1.75	-3.3
	(0.57)	(-0.07)	(0.67)	(-0.04)	(0.93)	(0.63)	(0.67)	(0.75)	(-0.88)	(-1.3)	(-0.29)	(-1.29)
$\text{CAAR}_{t=(21)}$	0.62	-0.41	0.26	-0.22	4.37	4.26	3.55	4.56	-2.86	-4.2	-2.62	-4.13
	(0.38)	(-0.18)	(0.54)	(-0.13)	(1.15)	(0.89)	(0.87)	(1.04)	(-1.36)	(-1.61)	(-0.76)	(-1.62)
$\text{CAAR}_{t=(22)}$	0.45	-0.44	0.19	-0.53	4.64	4.62	3.94	5.01	-3.55	-4.69	-3.18	-5.28
	(0.44)	(-0.02)	(0.59)	(-0.07)	(1.34)	(1.18)	(0.99)	(1.29)	(-1.43)	(-1.51)	(-0.8)	(-1.67)
N	37	37	37	37	21	21	21	21	18	18	18	18

Table XIX. CAAR for Windstorm Ciara (ALL,HOME,FOR) BMP: In Table (X) we present unweighted average cumulative average abnormal excess abnormal returns (CAAR) in percentage points for all wildfires. CAAR are computed using expected returns are from the market model (Mkt) and the factor models ($3F$,$4F$,$5F$). The variance for the test statistic is computed over the cross section of cumulative abnormal returns (CAR) using the variance estimate by (Boehmer et al., 1991). The resulting t_{BMP} statistics are normally distributed and presented in brackets below the CAAR. N is the number of companies in the cross section and t is the day from the event date. Negative values are before and positive after the event date. The cross section of securities i CAAR is derived over several events. Returns over weekends are omitted, as such an event date during the weekend will be on the next trading day in the analysis. The columns under ALL, are all possible events related to the climate hazard independent from the facility location with respects to the headquarters. HOME means that we only compute CAAR for those companies, whose impacted facilities are in the same location of the public listed owner. FOREIGN is for those public listed owners whose impacted facilities are located abroad.

	ALL				HOME				FOREIGN			
t	Mkt	3F	4F	5F	Mkt	3F	4F	5F	Mkt	3F	4F	5F
$\text{CAAR}_{t=(-5)}$	-0.09	-0.16	-0.13	-0.1	-0.19	-0.18	-0.22	-0.1	0.0	-0.09	-0.01	-0.04
	(-4.15)	(-4.05)	(-4.19)	(-4.17)	(-3.65)	(-3.38)	(-3.9)	(-3.28)	(-4.1)	(-4.07)	(-3.9)	(-4.42)
$\text{CAAR}_{t=(-4)}$	-0.44	-0.55	-0.51	-0.41	-0.36	-0.36	-0.4	-0.26	-0.48	-0.61	-0.51	-0.44
	(-4.64)	(-4.56)	(-4.69)	(-4.7)	(-4.1)	(-3.88)	(-4.34)	(-3.83)	(-4.58)	(-4.55)	(-4.42)	(-4.91)
$\text{CAAR}_{t=(-3)}$	-1.16	-1.21	-1.19	-1.06	-0.75	-0.71	-0.74	-0.64	-1.52	-1.58	-1.52	-1.35
	(-5.19)	(-5.1)	(-5.24)	(-5.25)	(-4.71)	(-4.48)	(-4.95)	(-4.43)	(-5.01)	(-4.98)	(-4.85)	(-5.35)
$\text{CAAR}_{t=(-2)}$	-1.05	-1.05	-1.04	-1.02	-0.63	-0.56	-0.57	-0.31	-1.46	-1.43	-1.41	-1.63
	(-5.56)	(-5.5)	(-5.65)	(-5.64)	(-5.12)	(-4.92)	(-5.41)	(-4.86)	(-5.28)	(-5.27)	(-5.17)	(-5.66)
$\text{CAAR}_{t=(-1)}$	-1.31	-1.27	-1.27	-1.32	-0.71	-0.61	-0.62	-0.27	-1.96	-1.87	-1.85	-2.33
	(-6.12)	(-6.07)	(-6.25)	(-6.18)	(-5.64)	(-5.43)	(-5.96)	(-5.45)	(-5.8)	(-5.82)	(-5.73)	(-6.08)
$\text{CAAR}_{t=(0)}$	-1.64	-1.67	-1.63	-1.73	-1.1	-1.03	-1.07	-0.61	-2.23	-2.24	-2.14	-2.82
	(-6.51)	(-6.48)	(-6.65)	(-6.56)	(-6.02)	(-5.82)	(-6.35)	(-5.86)	(-6.13)	(-6.18)	(-6.08)	(-6.36)
$\text{CAAR}_{t=(1)}$	-2.14	-2.09	-2.08	-2.19	-1.7	-1.62	-1.64	-1.12	-2.58	-2.49	-2.46	-3.24
	(-6.87)	(-6.82)	(-6.97)	(-6.91)	(-6.35)	(-6.14)	(-6.61)	(-6.21)	(-6.47)	(-6.51)	(-6.41)	(-6.66)
$\text{CAAR}_{t=(2)}$	-2.6	-2.42	-2.45	-2.53	-1.97	-1.86	-1.83	-1.46	-3.2	-2.94	-3.0	-3.59
	(-7.2)	(-7.16)	(-7.29)	(-7.22)	(-6.66)	(-6.45)	(-6.91)	(-6.53)	(-6.76)	(-6.8)	(-6.69)	(-6.91)
$\text{CAAR}_{t=(3)}$	-2.76	-2.54	-2.57	-2.71	-2.06	-1.93	-1.9	-1.47	-3.51	-3.18	-3.26	-4.02
	(-7.49)	(-7.47)	(-7.64)	(-7.51)	(-7.01)	(-6.78)	(-7.31)	(-6.8)	(-6.96)	(-7.03)	(-6.95)	(-7.19)
$\text{CAAR}_{t=(4)}$	-3.22	-2.93	-2.98	-3.0	-2.49	-2.34	-2.29	-1.84	-4.02	-3.59	-3.71	-4.28
	(-7.79)	(-7.78)	(-7.95)	(-7.81)	(-7.3)	(-7.06)	(-7.59)	(-7.1)	(-7.23)	(-7.33)	(-7.25)	(-7.43)
$\text{CAAR}_{t=(5)}$	-3.16	-2.83	-2.89	-2.94	-2.52	-2.36	-2.3	-1.84	-3.85	-3.37	-3.51	-4.16
	(-8.01)	(-8.03)	(-8.2)	(-8.07)	(-7.5)	(-7.26)	(-7.8)	(-7.31)	(-7.44)	(-7.57)	(-7.48)	(-7.69)
$\text{CAAR}_{t=(6)}$	-3.05	-2.8	-2.82	-2.9	-2.88	-2.73	-2.72	-2.24	-3.36	-2.99	-3.03	-3.74
	(-8.33)	(-8.36)	(-8.52)	(-8.39)	(-7.77)	(-7.53)	(-8.07)	(-7.58)	(-7.77)	(-7.92)	(-7.84)	(-8.02)
$\text{CAAR}_{t=(7)}$	-2.7	-2.61	-2.56	-2.64	-2.53	-2.43	-2.47	-1.95	-3.08	-2.93	-2.83	-3.51
	(-8.6)	(-8.61)	(-8.79)	(-8.64)	(-7.94)	(-7.68)	(-8.22)	(-7.73)	(-8.08)	(-8.21)	(-8.15)	(-8.32)
$\text{CAAR}_{t=(8)}$	-3.99	-3.78	-3.76	-3.71	-3.09	-2.96	-2.97	-2.55	-5.02	-4.71	-4.68	-5.0
	(-8.89)	(-8.88)	(-9.04)	(-8.92)	(-8.22)	(-7.99)	(-8.45)	(-8.02)	(-8.32)	(-8.42)	(-8.39)	(-8.55)
$\text{CAAR}_{t=(9)}$	-3.49	-3.29	-3.27	-3.24	-2.72	-2.6	-2.62	-2.11	-4.4	-4.11	-4.05	-4.53
	(-8.95)	(-8.95)	(-9.12)	(-9.0)	(-8.36)	(-8.1)	(-8.59)	(-8.12)	(-8.31)	(-8.44)	(-8.41)	(-8.61)
$\text{CAAR}_{t=(10)}$	-3.23	-3.01	-2.96	-3.04	-2.0	-1.82	-1.87	-1.32	-4.64	-4.28	-4.17	-4.89
	(-9.14)	(-9.14)	(-9.32)	(-9.18)	(-8.49)	(-8.24)	(-8.72)	(-8.28)	(-8.54)	(-8.67)	(-8.66)	(-8.8)
$\text{CAAR}_{t=(11)}$	-3.74	-3.54	-3.46	-3.61	-2.15	-1.98	-2.06	-1.59	-5.42	-5.1	-4.93	-5.68
	(-9.24)	(-9.29)	(-9.45)	(-9.31)	(-8.67)	(-8.47)	(-8.92)	(-8.51)	(-8.56)	(-8.73)	(-8.72)	(-8.83)
$\text{CAAR}_{t=(12)}$	-3.66	-3.42	-3.36	-3.51	-1.77	-1.56	-1.64	-1.24	-5.65	-5.27	-5.11	-5.8
	(-9.27)	(-9.3)	(-9.45)	(-9.33)	(-8.75)	(-8.55)	(-8.96)	(-8.58)	(-8.56)	(-8.71)	(-8.71)	(-8.82)
$\text{CAAR}_{t=(13)}$	-3.0	-2.79	-2.68	-2.78	-1.11	-0.89	-1.0	-0.68	-5.01	-4.66	-4.41	-4.87
	(-9.23)	(-9.29)	(-9.44)	(-9.3)	(-8.77)	(-8.58)	(-8.99)	(-8.59)	(-8.48)	(-8.66)	(-8.66)	(-8.78)
$\text{CAAR}_{t=(14)}$	-2.43	-2.23	-2.1	-2.11	0.47	0.7	0.56	0.75	-5.43	-5.08	-4.78	-4.91
	(-9.23)	(-9.3)	(-9.44)	(-9.33)	(-8.76)	(-8.59)	(-8.98)	(-8.61)	(-8.49)	(-8.68)	(-8.69)	(-8.83)
$\text{CAAR}_{t=(15)}$	-1.2	-1.24	-1.02	-1.18	0.88	1.04	0.82	1.21	-3.37	-3.36	-2.86	-3.44
	(-9.13)	(-9.19)	(-9.33)	(-9.26)	(-8.77)	(-8.61)	(-8.97)	(-8.62)	(-8.31)	(-8.49)	(-8.51)	(-8.69)
$\text{CAAR}_{t=(16)}$	-2.09	-2.4	-2.09	-2.27	-0.01	0.02	-0.31	0.2	-4.37	-4.75	-4.02	-4.67
	(-8.97)	(-9.02)	(-9.13)	(-9.07)	(-8.53)	(-8.4)	(-8.71)	(-8.44)	(-8.24)	(-8.39)	(-8.41)	(-8.54)
$\text{CAAR}_{t=(17)}$	-1.62	-2.0	-1.67	-1.9	-0.53	-0.47	-0.82	-0.23	-3.08	-3.54	-2.76	-3.6
	(-8.53)	(-8.52)	(-8.64)	(-8.58)	(-8.11)	(-7.95)	(-8.22)	(-8.0)	(-7.83)	(-7.89)	(-7.95)	(-8.05)
$\text{CAAR}_{t=(18)}$	-0.92	-1.45	-1.05	-1.44	0.29	0.32	-0.1	0.69	-2.53	-3.18	-2.25	-3.55
	(-8.14)	(-8.12)	(-8.24)	(-8.17)	(-7.67)	(-7.52)	(-7.77)	(-7.57)	(-7.5)	(-7.57)	(-7.64)	(-7.71)
$\text{CAAR}_{t=(19)}$	0.14	-0.39	0.03	-0.28	1.83	1.87	1.42	2.15	-1.79	-2.45	-1.45	-2.53
	(-7.6)	(-7.58)	(-7.66)	(-7.62)	(-7.19)	(-7.07)	(-7.23)	(-7.12)	(-6.99)	(-7.04)	(-7.1)	(-7.14)
$\text{CAAR}_{t=(20)}$	0.95	-0.23	0.47	-0.09	3.65	3.49	2.74	3.66	-1.86	-3.42	-1.75	-3.3
	(-6.88)	(-6.87)	(-6.93)	(-6.9)	(-6.54)	(-6.43)	(-6.58)	(-6.47)	(-6.31)	(-6.35)	(-6.41)	(-6.46)
$\text{CAAR}_{t=(21)}$	0.62	-0.41	0.26	-0.22	4.37	4.26	3.55	4.56	-2.86	-4.2	-2.62	-4.13
	(-5.81)	(-5.77)	(-5.83)	(-5.81)	(-5.58)	(-5.47)	(-5.56)	(-5.5)	(-5.29)	(-5.29)	(-5.39)	(-5.39)
$\text{CAAR}_{t=(22)}$	0.45	-0.44	0.19	-0.53	4.64	4.62	3.94	5.01	-3.55	-4.69	-3.18	-5.28
	(-4.22)	(-4.2)	(-4.24)	(-4.23)	(-4.08)	(-4.01)	(-4.07)	(-4.04)	(-3.82)	(-3.83)	(-3.9)	(-3.9)
N	37	37	37	37	21	21	21	21	18	18	18	18

Table XX. CAAR for Windstorm Ciara (ALL,HOME,FOR) CORR: In Table (X) we present unweighted average cumulative average abnormal excess abnormal returns (CAAR) in percentage points for all wildfires. CAAR are computed using expected returns are from the market model (Mkt) and the factor models ($3F$,$4F$,$5F$). The variance for the test statistic is computed over the cross section of cumulative abnormal returns (CAR) using the variance estimate by (Boehmer et al., 1991). The resulting t_{BMP} statistics are normally distributed and presented in brackets below the CAAR. N is the number of companies in the cross section and t is the day from the event date. Negative values are before and positive after the event date. The cross section of securities i CAAR is derived over several events. Returns over weekends are omitted, as such an event date during the weekend will be on the next trading day in the analysis. The columns under ALL, are all possible events related to the climate hazard independent from the facility location with respects to the headquarters. HOME means that we only compute CAAR for those companies, whose impacted facilities are in the same location of the public listed owner. FOREIGN is for those public listed owners whose impacted facilities are located abroad.

	ALL				HOME				FOREIGN			
	Mkt	3F	4F	5F	Mkt	3F	4F	5F	Mkt	3F	4F	5F
t												
$\text{CAAR}_{t=(-2)}$	0.08	0.07	0.03	0.11	-0.5	-0.59	-0.62	-0.58	0.34	0.36	0.33	0.42
	(-0.1)	(-0.33)	(-0.4)	(-0.07)	(-1.43)	(-1.73)	(-1.87)	(-1.79)	(1.63)	(1.38)	(1.35)	(1.68)
$\text{CAAR}_{t=(-1)}$	0.09	0.04	0.01	0.06	-0.53	-0.64	-0.64	-0.74	0.37	0.34	0.31	0.41
	(-0.41)	(-0.63)	(-0.66)	(-0.47)	(-0.91)	(-1.18)	(-1.19)	(-1.29)	(1.02)	(0.92)	(0.92)	(1.19)
$\text{CAAR}_{t=(0)}$	-0.38	-0.31	-0.27	-0.24	-1.79	-1.93	-1.88	-1.98	0.24	0.41	0.44	0.54
	(-1.4)	(-1.06)	(-0.94)	(-0.75)	(-1.94)	(-2.17)	(-2.13)	(-2.38)	(0.88)	(1.48)	(1.5)	(2.1)
$\text{CAAR}_{t=(1)}$	-0.4	-0.26	-0.18	-0.13	-1.5	-1.53	-1.46	-1.37	0.09	0.31	0.38	0.42
	(-1.69)	(-0.85)	(-0.64)	(-0.31)	(-2.34)	(-2.15)	(-2.07)	(-1.96)	(0.66)	(1.67)	(1.62)	(2.22)
$\text{CAAR}_{t=(2)}$	-0.27	-0.03	-0.02	0.03	-1.17	-1.02	-0.99	-0.99	0.13	0.4	0.41	0.48
	(-1.64)	(-0.74)	(-0.67)	(-0.4)	(-2.4)	(-1.81)	(-1.71)	(-1.9)	(0.35)	(1.03)	(1.02)	(1.38)
$\text{CAAR}_{t=(3)}$	0.1	0.42	0.52	0.54	-0.23	0.06	0.2	0.15	0.24	0.57	0.66	0.72
	(-0.73)	(0.2)	(0.44)	(0.83)	(-1.05)	(-0.64)	(-0.37)	(-0.53)	(0.36)	(0.99)	(0.99)	(1.44)
$\text{CAAR}_{t=(4)}$	-0.1	0.28	0.44	0.38	-1.05	-0.48	-0.3	-0.45	0.33	0.61	0.77	0.74
	(-0.76)	(0.27)	(0.55)	(0.73)	(-2.3)	(-0.98)	(-0.63)	(-0.78)	(0.49)	(1.09)	(1.1)	(1.45)
$\text{CAAR}_{t=(5)}$	-0.43	0.01	0.15	0.09	-1.57	-1.09	-0.94	-1.16	0.08	0.5	0.64	0.64
	(-1.41)	(-0.41)	(-0.15)	(-0.01)	(-2.77)	(-2.03)	(-1.59)	(-1.8)	(0.19)	(0.85)	(0.87)	(1.17)
$\text{CAAR}_{t=(6)}$	-0.82	-0.34	-0.06	-0.25	-1.66	-1.04	-0.76	-1.0	-0.45	-0.03	0.26	0.09
	(-1.6)	(-0.57)	(-0.1)	(-0.13)	(-1.9)	(-1.43)	(-1.03)	(-1.11)	(-0.59)	(0.16)	(0.38)	(0.48)
$\text{CAAR}_{t=(7)}$	-0.89	-0.39	-0.19	-0.23	-2.79	-2.03	-1.87	-1.96	-0.04	0.34	0.56	0.54
	(-1.95)	(-0.82)	(-0.49)	(-0.22)	(-9.53)	(-2.53)	(-2.02)	(-1.89)	(-0.36)	(0.25)	(0.41)	(0.62)
$\text{CAAR}_{t=(8)}$	-1.01	-0.29	-0.14	-0.06	-2.08	-1.07	-0.97	-0.57	-0.53	0.06	0.23	0.17
	(-2.87)	(-1.26)	(-0.94)	(-0.42)	(-9.08)	(-1.4)	(-1.04)	(-0.37)	(-0.9)	(-0.23)	(-0.08)	(0.16)
$\text{CAAR}_{t=(9)}$	-1.44	-0.7	-0.61	-0.42	-3.01	-1.86	-1.81	-1.47	-0.74	-0.18	-0.08	0.05
	(-3.25)	(-1.87)	(-1.69)	(-0.84)	(-3.65)	(-2.19)	(-1.94)	(-1.76)	(-1.05)	(-0.16)	(-0.03)	(0.45)
$\text{CAAR}_{t=(10)}$	-1.42	-0.65	-0.59	-0.42	-3.24	-2.01	-1.97	-1.78	-0.61	-0.05	0.02	0.18
	(-3.31)	(-1.77)	(-1.6)	(-0.92)	(-4.94)	(-3.54)	(-3.28)	(-3.2)	(-1.04)	(-0.16)	(-0.04)	(0.41)
$\text{CAAR}_{t=(11)}$	-1.33	-0.72	-0.71	-0.49	-4.42	-3.48	-3.48	-3.28	0.05	0.5	0.52	0.75
	(-1.56)	(-0.84)	(-0.82)	(-0.33)	(-4.89)	(-3.91)	(-3.87)	(-3.68)	(0.34)	(0.8)	(0.87)	(1.21)
$\text{CAAR}_{t=(12)}$	-1.67	-1.02	-0.91	-0.78	-5.69	-4.62	-4.48	-4.16	0.11	0.58	0.68	0.72
	(-1.76)	(-0.93)	(-0.8)	(-0.44)	(-7.61)	(-5.9)	(-5.48)	(-4.92)	(0.53)	(1.02)	(1.11)	(1.41)
$\text{CAAR}_{t=(13)}$	-1.28	-0.5	-0.34	-0.23	-4.5	-3.29	-3.14	-2.72	0.14	0.74	0.91	0.87
	(-1.46)	(-0.31)	(-0.15)	(0.18)	(-5.12)	(-2.72)	(-2.44)	(-2.35)	(0.54)	(1.05)	(1.13)	(1.39)
$\text{CAAR}_{t=(14)}$	-1.13	-0.28	-0.26	0.03	-3.74	-2.66	-2.66	-2.01	0.03	0.78	0.82	0.93
	(-1.05)	(0.11)	(0.13)	(0.65)	(-3.42)	(-2.02)	(-1.94)	(-1.62)	(0.59)	(1.25)	(1.24)	(1.53)
$\text{CAAR}_{t=(15)}$	-1.18	-0.36	-0.35	-0.12	-3.8	-2.74	-2.68	-2.16	-0.02	0.69	0.69	0.79
	(-0.88)	(0.14)	(0.15)	(0.57)	(-3.31)	(-2.46)	(-2.36)	(-2.1)	(0.73)	(1.25)	(1.21)	(1.46)
$\text{CAAR}_{t=(16)}$	-1.04	-0.14	-0.02	0.09	-4.12	-2.94	-2.77	-2.3	0.33	1.1	1.21	1.16
	(-0.46)	(0.56)	(0.64)	(0.92)	(-3.84)	(-2.61)	(-2.29)	(-2.2)	(1.04)	(1.6)	(1.57)	(1.81)
$\text{CAAR}_{t=(17)}$	-0.51	0.41	0.52	0.69	-3.81	-2.53	-2.41	-1.65	0.95	1.71	1.82	1.73
	(0.06)	(1.13)	(1.2)	(1.57)	(-3.61)	(-2.06)	(-1.79)	(-1.5)	(1.54)	(1.99)	(1.95)	(2.19)
$\text{CAAR}_{t=(18)}$	0.01	1.02	1.24	1.32	-3.24	-1.75	-1.51	-0.82	1.46	2.25	2.47	2.27
	(0.52)	(1.78)	(1.93)	(2.28)	(-2.72)	(-1.38)	(-1.04)	(-0.77)	(1.87)	(2.29)	(2.27)	(2.5)
$\text{CAAR}_{t=(19)}$	0.47	1.61	1.84	1.85	-3.19	-1.32	-1.08	-0.7	2.1	2.91	3.15	2.99
	(0.67)	(2.16)	(2.25)	(2.66)	(-2.2)	(-0.82)	(-0.56)	(-0.47)	(2.04)	(2.53)	(2.47)	(2.92)
$\text{CAAR}_{t=(20)}$	0.71	2.01	2.24	2.27	-2.88	-0.84	-0.62	-0.25	2.3	3.27	3.51	3.38
	(0.85)	(2.48)	(2.52)	(3.01)	(-1.8)	(-0.39)	(-0.21)	(-0.08)	(2.05)	(2.59)	(2.52)	(2.99)
$\text{CAAR}_{t=(21)}$	1.59	3.08	3.25	3.33	-2.89	-0.32	-0.18	0.3	3.58	4.6	4.77	4.68
	(1.48)	(3.11)	(3.08)	(3.45)	(-1.41)	(0.18)	(0.25)	(0.45)	(2.65)	(3.27)	(3.16)	(3.54)
$\text{CAAR}_{t=(22)}$	2.53	4.18	4.34	4.52	-2.68	0.12	0.26	1.02	4.85	5.98	6.16	6.07
	(2.1)	(3.94)	(3.89)	(4.39)	(-1.54)	(0.45)	(0.51)	(0.92)	(3.12)	(3.93)	(3.78)	(4.12)
N	13	13	13	13	4	4	4	4	9	9	9	9

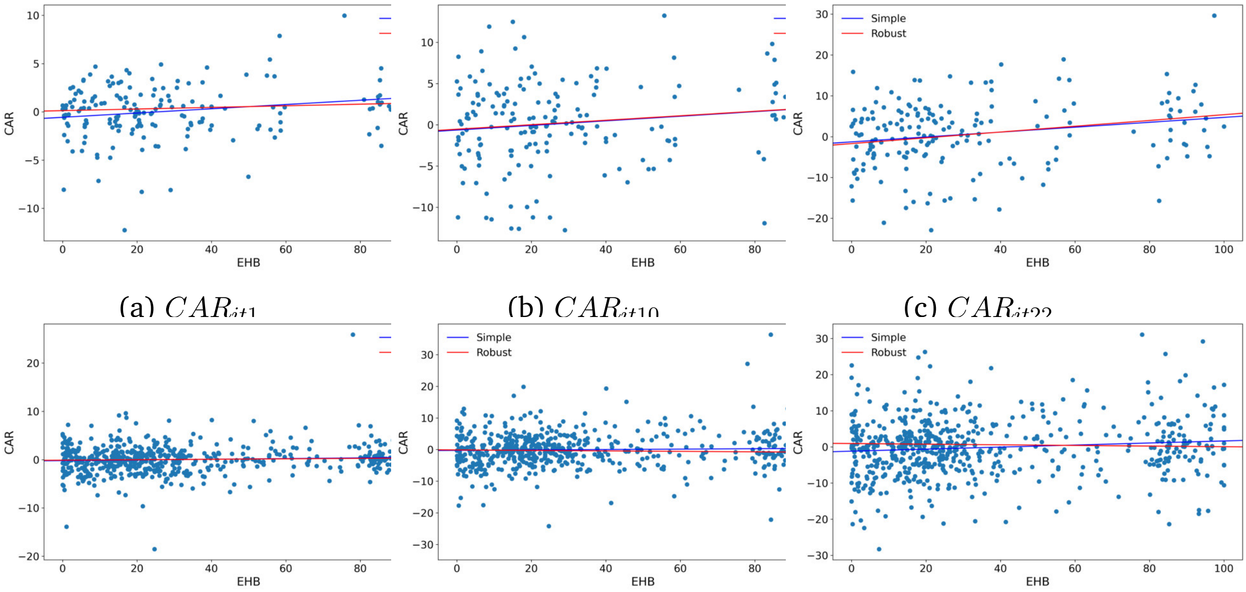
Table XXI. CAAR for Wildfires 2017 (ALL,HOME,FOR) BMP: In Table (X) we present unweighted average cumulative average abnormal excess abnormal returns (CAAR) in percentage points for all wildfires. CAAR are computed using expected returns are from the market model (Mkt) and the factor models ($3F$,$4F$,$5F$). The variance for the test statistic is computed over the cross section of cumulative abnormal returns (CAR) using the variance estimate by (Boehmer et al., 1991). The resulting t_{BMP} statistics are normally distributed and presented in brackets below the CAAR. N is the number of companies in the cross section and t is the day from the event date. Negative values are before and positive after the event date. The cross section of securities i CAAR is derived over several events. Returns over weekends are omitted, as such an event date during the weekend will be on the next trading day in the analysis. The columns under ALL, are all possible events related to the climate hazard independent from the facility location with respects to the headquarters. HOME means that we only compute CAAR for those companies, whose impacted facilities are in the same location of the public listed owner. FOREIGN is for those public listed owners whose impacted facilities are located abroad.

	ALL				HOME				FOREIGN			
t	Mkt	3F	4F	5F	Mkt	3F	4F	5F	Mkt	3F	4F	5F
$\text{CAAR}_{t=(-2)}$	0.08	0.07	0.03	0.11	-0.5	-0.59	-0.62	-0.58	0.34	0.36	0.33	0.42
	(-3.04)	(-2.44)	(-2.41)	(-2.29)	(-3.53)	(-2.74)	(-2.82)	(-2.5)	(-2.26)	(-1.84)	(-1.77)	(-1.73)
$\text{CAAR}_{t=(-1)}$	0.09	0.04	0.01	0.06	-0.53	-0.64	-0.64	-0.74	0.37	0.34	0.31	0.41
	(-3.79)	(-3.13)	(-3.09)	(-2.99)	(-3.95)	(-3.12)	(-3.19)	(-2.86)	(-3.04)	(-2.56)	(-2.46)	(-2.47)
$\text{CAAR}_{t=(0)}$	-0.38	-0.31	-0.27	-0.24	-1.79	-1.93	-1.88	-1.98	0.24	0.41	0.44	0.54
	(-4.43)	(-3.77)	(-3.72)	(-3.62)	(-4.47)	(-3.65)	(-3.72)	(-3.34)	(-3.63)	(-3.14)	(-3.03)	(-3.05)
$\text{CAAR}_{t=(1)}$	-0.4	-0.26	-0.18	-0.13	-1.5	-1.53	-1.46	-1.37	0.09	0.31	0.38	0.42
	(-4.88)	(-4.3)	(-4.29)	(-4.17)	(-4.62)	(-3.78)	(-3.88)	(-3.47)	(-4.15)	(-3.77)	(-3.7)	(-3.7)
$\text{CAAR}_{t=(2)}$	-0.27	-0.03	-0.02	0.03	-1.17	-1.02	-0.99	-0.99	0.13	0.4	0.41	0.48
	(-5.45)	(-4.92)	(-4.92)	(-4.82)	(-5.15)	(-4.38)	(-4.48)	(-4.16)	(-4.64)	(-4.28)	(-4.23)	(-4.21)
$\text{CAAR}_{t=(3)}$	0.1	0.42	0.52	0.54	-0.23	0.06	0.2	0.15	0.24	0.57	0.66	0.72
	(-6.07)	(-5.54)	(-5.52)	(-5.43)	(-5.68)	(-4.97)	(-5.07)	(-4.69)	(-5.19)	(-4.81)	(-4.72)	(-4.74)
$\text{CAAR}_{t=(4)}$	-0.1	0.28	0.44	0.38	-1.05	-0.48	-0.3	-0.45	0.33	0.61	0.77	0.74
	(-6.66)	(-6.17)	(-6.17)	(-6.07)	(-6.31)	(-5.61)	(-5.73)	(-5.35)	(-5.66)	(-5.31)	(-5.25)	(-5.24)
$\text{CAAR}_{t=(5)}$	-0.43	0.01	0.15	0.09	-1.57	-1.09	-0.94	-1.16	0.08	0.5	0.64	0.64
	(-7.05)	(-6.63)	(-6.65)	(-6.53)	(-6.5)	(-5.92)	(-6.02)	(-5.62)	(-6.09)	(-5.77)	(-5.73)	(-5.71)
$\text{CAAR}_{t=(6)}$	-0.82	-0.34	-0.06	-0.25	-1.66	-1.04	-0.76	-1.0	-0.45	-0.03	0.26	0.09
	(-7.34)	(-6.94)	(-6.96)	(-6.84)	(-6.65)	(-6.03)	(-6.12)	(-5.69)	(-6.39)	(-6.12)	(-6.09)	(-6.09)
$\text{CAAR}_{t=(7)}$	-0.89	-0.39	-0.19	-0.23	-2.79	-2.03	-1.87	-1.96	-0.04	0.34	0.56	0.54
	(-7.64)	(-7.25)	(-7.31)	(-7.17)	(-6.93)	(-6.39)	(-6.5)	(-6.07)	(-6.65)	(-6.35)	(-6.36)	(-6.32)
$\text{CAAR}_{t=(8)}$	-1.01	-0.29	-0.14	-0.06	-2.08	-1.07	-0.97	-0.57	-0.53	0.06	0.23	0.17
	(-7.99)	(-7.58)	(-7.61)	(-7.54)	(-7.08)	(-6.56)	(-6.62)	(-6.27)	(-7.04)	(-6.7)	(-6.69)	(-6.71)
$\text{CAAR}_{t=(9)}$	-1.44	-0.7	-0.61	-0.42	-3.01	-1.86	-1.81	-1.47	-0.74	-0.18	-0.08	0.05
	(-8.22)	(-7.87)	(-7.88)	(-7.84)	(-7.47)	(-7.03)	(-7.06)	(-6.78)	(-7.14)	(-6.84)	(-6.82)	(-6.84)
$\text{CAAR}_{t=(10)}$	-1.42	-0.65	-0.59	-0.42	-3.24	-2.01	-1.97	-1.78	-0.61	-0.05	0.02	0.18
	(-8.42)	(-8.03)	(-8.02)	(-8.01)	(-7.46)	(-7.01)	(-7.02)	(-6.74)	(-7.42)	(-7.07)	(-7.03)	(-7.1)
$\text{CAAR}_{t=(11)}$	-1.33	-0.72	-0.71	-0.49	-4.42	-3.48	-3.48	-3.28	0.05	0.5	0.52	0.75
	(-8.61)	(-8.25)	(-8.23)	(-8.2)	(-7.54)	(-7.11)	(-7.11)	(-6.8)	(-7.63)	(-7.3)	(-7.26)	(-7.32)
$\text{CAAR}_{t=(12)}$	-1.67	-1.02	-0.91	-0.78	-5.69	-4.62	-4.48	-4.16	0.11	0.58	0.68	0.72
	(-8.79)	(-8.4)	(-8.37)	(-8.36)	(-7.45)	(-7.02)	(-7.01)	(-6.72)	(-7.91)	(-7.55)	(-7.49)	(-7.57)
$\text{CAAR}_{t=(13)}$	-1.28	-0.5	-0.34	-0.23	-4.5	-3.29	-3.14	-2.72	0.14	0.74	0.91	0.87
	(-8.81)	(-8.46)	(-8.46)	(-8.42)	(-7.25)	(-6.86)	(-6.87)	(-6.6)	(-8.04)	(-7.71)	(-7.68)	(-7.7)
$\text{CAAR}_{t=(14)}$	-1.13	-0.28	-0.26	0.03	-3.74	-2.66	-2.66	-2.01	0.03	0.78	0.82	0.93
	(-8.93)	(-8.61)	(-8.61)	(-8.58)	(-7.48)	(-7.09)	(-7.09)	(-6.86)	(-8.08)	(-7.79)	(-7.77)	(-7.78)
$\text{CAAR}_{t=(15)}$	-1.18	-0.36	-0.35	-0.12	-3.8	-2.74	-2.68	-2.16	-0.02	0.69	0.69	0.79
	(-8.9)	(-8.61)	(-8.57)	(-8.6)	(-7.53)	(-7.13)	(-7.11)	(-6.94)	(-8.01)	(-7.76)	(-7.71)	(-7.76)
$\text{CAAR}_{t=(16)}$	-1.04	-0.14	-0.02	0.09	-4.12	-2.94	-2.77	-2.3	0.33	1.1	1.21	1.16
	(-8.72)	(-8.43)	(-8.4)	(-8.4)	(-7.33)	(-6.97)	(-6.96)	(-6.76)	(-7.87)	(-7.61)	(-7.55)	(-7.6)
$\text{CAAR}_{t=(17)}$	-0.51	0.41	0.52	0.69	-3.81	-2.53	-2.41	-1.65	0.95	1.71	1.82	1.73
	(-8.44)	(-8.2)	(-8.19)	(-8.17)	(-7.02)	(-6.69)	(-6.72)	(-6.5)	(-7.67)	(-7.45)	(-7.4)	(-7.43)
$\text{CAAR}_{t=(18)}$	0.01	1.02	1.24	1.32	-3.24	-1.75	-1.51	-0.82	1.46	2.25	2.47	2.27
	(-8.15)	(-7.92)	(-7.9)	(-7.9)	(-6.75)	(-6.46)	(-6.46)	(-6.3)	(-7.42)	(-7.19)	(-7.15)	(-7.17)
$\text{CAAR}_{t=(19)}$	0.47	1.61	1.84	1.85	-3.19	-1.32	-1.08	-0.7	2.1	2.91	3.15	2.99
	(-7.67)	(-7.48)	(-7.47)	(-7.46)	(-6.36)	(-6.1)	(-6.11)	(-5.96)	(-6.98)	(-6.79)	(-6.76)	(-6.77)
$\text{CAAR}_{t=(20)}$	0.71	2.01	2.24	2.27	-2.88	-0.84	-0.62	-0.25	2.3	3.27	3.51	3.38
	(-6.93)	(-6.8)	(-6.79)	(-6.78)	(-5.69)	(-5.54)	(-5.54)	(-5.38)	(-6.33)	(-6.18)	(-6.15)	(-6.17)
$\text{CAAR}_{t=(21)}$	1.59	3.08	3.25	3.33	-2.89	-0.32	-0.18	0.3	3.58	4.6	4.77	4.68
	(-5.9)	(-5.81)	(-5.79)	(-5.8)	(-4.85)	(-4.73)	(-4.73)	(-4.6)	(-5.38)	(-5.28)	(-5.25)	(-5.28)
$\text{CAAR}_{t=(22)}$	2.53	4.18	4.34	4.52	-2.68	0.12	0.26	1.02	4.85	5.98	6.16	6.07
	(-4.36)	(-4.31)	(-4.3)	(-4.3)	(-3.55)	(-3.5)	(-3.5)	(-3.41)	(-3.99)	(-3.92)	(-3.9)	(-3.92)
N	13	13	13	13	4	4	4	4	9	9	9	9

Table XXII. CAAR for Wildfires 2017 (ALL,HOME,FOR) Corrado rank test: In Table (X) we present unweighted average cumulative average abnormal excess abnormal returns (CAAR) in percentage points for all wildfires. CAAR are computed using expected returns are from the market model (Mkt) and the factor models ($3F$,$4F$,$5F$). The variance for the test statistic is computed over the cross section of cumulative abnormal returns (CAR) using the variance estimate by (Boehmer et al., 1991). The resulting t_{BMP} statistics are normally distributed and presented in brackets below the CAAR. N is the number of companies in the cross section and t is the day from the event date. Negative values are before and positive after the event date. The cross section of securities i CAAR is derived over several events. Returns over weekends are omitted, as such an event date during the weekend will be on the next trading day in the analysis. The columns under ALL, are all possible events related to the climate hazard independent from the facility location with respects to the headquarters. HOME means that we only compute CAAR for those companies, whose impacted facilities are in the same location of the public listed owner. FOREIGN is for those public listed owners whose impacted facilities are located abroad.

E.d EHB regressions for wildfires and floods

We visualise the impact of this method on the regression result in Figure (20) to avoid any concerns. Here is visible for wildfires and floods that the regression of EHB_{it} on $CAR_{it\Delta}$ would suffer from outliers. The blue line is the simple OLS regression, and the red line is the robust estimator. The difference is minimal in both regressions.



(a) CAR_{it1} (b) CAR_{it10} (c) CAR_{it22}

(d) CAR_{it1} (e) CAR_{it10} (f) CAR_{it22}

Figure 20. Scatter Plots of EHB on $CAR_{it\Delta}$ for wildfires and floods: In Sub-Figure (20a,20b,20c) we provide a scatterplots of $CAAR$ on EHB and a line fit for the the OLS and the robust linear estimator for Wildfires (WF). In Sub-Figure (20d,20e,20f) we provide a scatterplots of $CAAR$ on EHB and a line fit for the the OLS and the robust linear estimator for Floods.

In the realm of wildfires, our analysis continues to elucidate the role of home bias in shaping market reactions, as highlighted in Table (XXIII). Analogous to the winter windstorms context, the influence of home bias on CAR remains robust across diverse time spans. Across all regression iterations, the findings consistently demonstrate a positive and statistically significant correlation between home bias and CAR. The observed impact manifests similarly to that of winter windstorms, with an additional unit of home bias associated with an increase of CAR ranging from 0.02% to 0.08%, contingent upon the temporal distance from the event. This empirical consistency underlines the potential of home bias as a driver of market adjustments in the wake of adverse events such as wildfires.

Turning our attention to floods, the relationship between home bias and CAR becomes less straightforward. As elucidated in Table (XXXI), the results exhibit variability across different regressions, with some specifications failing to yield statistically significant results. Moreover, the explanatory power of these regressions remains limited, with poor model fit observed in multiple instances. This intricacy complicates the interpretation of the findings, making it challenging to draw conclusive inferences regarding the influence of home bias on market reactions to flood events. The lack of consistent and significant results, along with the subpar explanatory ability of the regressions, calls for caution in formulating definitive conclusions

	Dependent variable: $CAR_{it\Delta}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
β_0	-0.56*	0.40	0.56	-0.64	-2.00	-4.52***	-1.29	-6.67	-4.86**
	(0.31)	(2.23)	(0.82)	(0.55)	(4.27)	(1.70)	(0.87)	(6.76)	(2.15)
EHB	0.02***	0.03***	0.03***	0.03**	0.03	0.03***	0.06***	0.05	0.08***
	(0.01)	(0.01)	(0.00)	(0.01)	(0.02)	(0.01)	(0.02)	(0.04)	(0.01)
BM_t		-0.39	-0.29**		0.20	0.37		0.71	3.01***
		(0.39)	(0.14)		(0.74)	(0.29)		(1.14)	(0.36)
P_t		-0.36	-0.45***		0.45	1.22***		1.57	1.66***
		(0.44)	(0.16)		(0.83)	(0.33)		(1.22)	(0.39)
MC_t		0.03	-0.01		0.04	0.02		-0.14	-0.12
		(0.21)	(0.08)		(0.40)	(0.16)		(0.64)	(0.21)
σ_m		0.05	0.09***		0.05	0.06		0.10	0.17***
		(0.05)	(0.02)		(0.09)	(0.03)		(0.13)	(0.04)
MOM		-0.00	-0.01**		-0.02	-0.04***		-0.01	-0.00
		(0.01)	(0.00)		(0.02)	(0.01)		(0.03)	(0.01)
TURN		-2.14**	-1.85***		-0.53	0.55		3.16	-1.89**
		(1.05)	(0.39)		(1.78)	(0.71)		(2.62)	(0.84)
Observations	185	114	114	185	113	113	185	115	115
R^2	0.05	0.11		0.03	0.04		0.05	0.09	
Adjusted R^2	0.05	0.05		0.02	-0.02		0.04	0.03	
Note:	*p<0.1; **p<0.05; ***p<0.01								

Table XXIII. EHB regressions for companies impacted by wildfires: from columns (1) to (3) we provide regressions of the independent variables on CAR_{it1}, where in column (1) the indipendent variable is HB_{cr}, in column (2) we include controls and in column (3) we include a robust estimation accounting for outliers. Similar applies for columns (4) to (6) which are a regression on CAR_{it10} and columns (7) to (9) on CAR_{it22}.

regarding the relationship between home bias and CAR in the context of floods.

	Dependent variable: $CAR_{it\Delta}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
β_0	-0.20	2.25*	0.01	-0.25	4.17	4.17***	-1.18**	6.10*	10.49***
	(0.19)	(1.36)	(0.46)	(0.36)	(2.60)	(0.75)	(0.50)	(3.43)	(1.22)
EHB	0.01*	0.02**	0.01***	0.01	0.02*	0.02***	0.03***	0.06***	0.03***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.02)	(0.01)
BM_t		0.06	0.54***		0.06	1.12***		0.30	0.68***
		(0.29)	(0.10)		(0.54)	(0.16)		(0.70)	(0.25)
P_t		-0.30	-0.02		-0.79**	-0.55***		-0.93*	-0.84***
		(0.20)	(0.07)		(0.38)	(0.11)		(0.50)	(0.18)
MC_t		-0.10	0.11***		0.05	0.05		-0.38	-0.61***
		(0.12)	(0.04)		(0.24)	(0.07)		(0.31)	(0.11)
TURN		-0.20	-0.82***		0.04	-0.07		1.25	4.41***
		(0.48)	(0.16)		(0.92)	(0.26)		(1.24)	(0.44)
σ_m		-0.07**	-0.07***		-0.21***	-0.24***		-0.15**	-0.32***
		(0.03)	(0.01)		(0.05)	(0.02)		(0.07)	(0.03)
MOM		0.00	0.00**		0.00	0.01**		0.00	-0.02***
		(0.00)	(0.00)		(0.01)	(0.00)		(0.01)	(0.00)
Observations	598	285	285	598	287	287	598	286	286
R^2	0.00	0.07		0.00	0.08		0.01	0.12	
Adjusted R^2	0.00	0.04		-0.00	0.06		0.01	0.10	
Note:	*p<0.1; **p<0.05; ***p<0.01								

Table XXIV. EHB regressions for companies impacted by floods: from columns (1) to (3) we provide regressions of the independent variables on CAR_{it1}, where in column (1) the indipendent variable is EHB, in column (2) we include controls and in column (3) we include a robust estimation accounting for outliers. Similar applies for columns (4) to(6) which are a regression on CAR_{it10} and columns (7) to (9) on CAR_{it22}.

E.e Physical risk and Equity Home Bias regressions

	Dependent variable: $CAR_{it\triangle}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
β_0	-0.71**	1.05	3.80***	-1.22**	1.65	5.96***	0.10	5.01	3.61**
	(0.31)	(2.21)	(0.57)	(0.48)	(3.32)	(1.08)	(0.73)	(4.97)	(1.78)
WS_{EAL}	-0.22	-0.29	-0.02	-0.51	-0.51	-1.28***	-0.57	-0.44	-5.66***
	(0.58)	(0.71)	(0.18)	(0.90)	(1.07)	(0.35)	(1.38)	(1.60)	(0.57)
BM_t		-0.12	-0.04		0.01	0.23		1.20	-0.04
		(0.54)	(0.14)		(0.81)	(0.26)		(1.21)	(0.43)
P_t		-0.35	-0.48***		0.14	-0.13		0.15	-0.91***
		(0.41)	(0.11)		(0.61)	(0.20)		(0.91)	(0.33)
MC_t		-0.08	-0.31***		-0.33	-0.71***		-0.51	0.01
		(0.23)	(0.06)		(0.34)	(0.11)		(0.51)	(0.18)
σ_m		-0.01	-0.05***		-0.01	0.02		0.09	0.14***
		(0.03)	(0.01)		(0.05)	(0.02)		(0.08)	(0.03)
MOM		-0.01	-0.00		-0.01	-0.01*		0.03	0.02**
		(0.01)	(0.00)		(0.02)	(0.01)		(0.03)	(0.01)
TURN		0.57	0.54**		-0.44	-1.11**		-3.80*	-6.77***
		(0.93)	(0.24)		(1.40)	(0.45)		(2.09)	(0.75)
N	196	173	173	196	175	175	196	175	175
R^2	0.00	0.01		0.00	0.01		0.00	0.06	

Note: *p<0.1; **p<0.05; ***p<0.01

Table XXV. Windstorm risk regressions for companies impacted by WSfrom columns (1) to (3) we provide regressions of the independent variables on CAR_{it1}, where in column (1) the indipendent variable is WS_{EAL}, in column (2) we include controls and in column (3) we include a robust estimation accounting for outliers. Similar applies for columns (4) to(6) which are a regression on CAR_{it10} and columns (7) to (9) on CAR_{it22}.

	Dependent variable: $CAR_{it\triangle}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
β_0	-0.68**	0.97	3.79***	-1.16**	1.51	5.61***	0.18	4.89	0.64
	(0.31)	(2.19)	(0.57)	(0.47)	(3.29)	(1.08)	(0.72)	(4.93)	(1.89)
$WS_{ins_{EAL}}$	-15.28	-18.58	-0.22	-37.03	-44.09	-31.08**	-43.95	-56.32	-48.85**
	(20.81)	(26.31)	(6.80)	(31.94)	(39.50)	(12.92)	(48.95)	(59.12)	(22.64)
BM_t		-0.04	-0.04		0.20	0.01		1.44	-0.20
		(0.55)	(0.14)		(0.82)	(0.27)		(1.23)	(0.47)
P_t		-0.34	-0.48***		0.14	0.00		0.12	-0.59*
		(0.41)	(0.10)		(0.60)	(0.20)		(0.90)	(0.35)
MC_t		-0.07	-0.31***		-0.29	-0.73***		-0.46	0.15
		(0.23)	(0.06)		(0.34)	(0.11)		(0.51)	(0.19)
σ_m		-0.01	-0.05***		-0.01	0.03*		0.09	0.19***
		(0.03)	(0.01)		(0.05)	(0.02)		(0.08)	(0.03)
MOM		-0.00	-0.00		-0.01	-0.01**		0.03	0.01
		(0.01)	(0.00)		(0.02)	(0.01)		(0.03)	(0.01)
TURN		0.58	0.54**		-0.44	-2.31***		-3.81*	-6.64***
		(0.93)	(0.24)		(1.39)	(0.46)		(2.08)	(0.80)
N	196	173	173	196	175	175	196	175	175
R^2	0.00	0.01		0.01	0.02		0.00	0.07	

Note: *p<0.1; **p<0.05; ***p<0.01

Table XXVI. Windstorm risk regressions for companies impacted by WS with historical insurance coverage: from columns (1) to (3) we provide regressions of the independent variables on CAR_{it1}, where in column (1) the indipendent variable is HB_{cr}, in column (2) we include controls and in column (3) we include a robust estimation accounting for outliers. Similar applies for columns (4) to(6) which are a regression on CAR_{it10} and columns (7) to (9) on CAR_{it22}.

	Dependent variable: $CAR_{it\Delta}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
β_0	-2.01***	-2.05	-2.79***	-3.08***	-3.14	-3.52***	-0.64	0.30	0.43
	(0.51)	(2.31)	(0.67)	(0.78)	(3.46)	(1.16)	(1.19)	(5.21)	(2.04)
EHB	0.03***	0.03***	0.03***	0.04***	0.06***	0.07***	0.01	0.04	0.06***
	(0.01)	(0.01)	(0.00)	(0.02)	(0.02)	(0.01)	(0.02)	(0.03)	(0.01)
WS$_{EAL}$	-0.07	-0.74	-0.18	-1.47	-2.96	-4.19***	-3.16	-4.22	-15.71***
	(1.44)	(1.97)	(0.57)	(2.22)	(2.96)	(1.00)	(3.37)	(4.46)	(1.74)
WS$_{EAL} * EHB$	0.00	0.02	0.01	0.04	0.07	0.11***	0.09	0.11	0.40***
	(0.04)	(0.05)	(0.01)	(0.06)	(0.08)	(0.03)	(0.10)	(0.12)	(0.05)
BM$_t$		0.16	-0.46***		0.54	0.68**		1.72	2.33***
		(0.53)	(0.15)		(0.79)	(0.27)		(1.19)	(0.47)
P$_t$		-0.43	-0.17		-0.01	0.01		-0.06	-0.61*
		(0.40)	(0.11)		(0.59)	(0.20)		(0.89)	(0.35)
MC$_t$		0.17	0.11*		0.07	-0.02		0.00	0.36*
		(0.23)	(0.07)		(0.34)	(0.11)		(0.51)	(0.20)
σ_m		-0.00	-0.00		0.00	0.04**		0.07	0.03
		(0.03)	(0.01)		(0.05)	(0.02)		(0.08)	(0.03)
MOM		-0.01	-0.02***		-0.01	-0.00		0.02	-0.00
		(0.01)	(0.00)		(0.02)	(0.01)		(0.03)	(0.01)
TURN		0.01	-0.46*		-1.39	-1.79***		-4.28**	-6.50***
		(0.93)	(0.27)		(1.39)	(0.47)		(2.09)	(0.82)
N	195	172	172	195	174	174	195	174	174
R^2	0.05	0.07		0.05	0.08		0.01	0.06	

Note: *p<0.1; **p<0.05; ***p<0.01

Table XXVII. Windstorm risk and EHB regressions for companies impacted by WS: from columns (1) to (3) we provide regressions of the independent variables on CAR_{it1}, where in column (1) the indipendent variable is HB_{cr}, in column (2) we include controls and in column (3) we include a robust estimation accounting for outliers. Similar applies for columns (4) to(6) which are a regression on CAR_{it10} and columns (7) to (9) on CAR_{it22}.

	Dependent variable: $CAR_{it\Delta}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
β_0	0.17	3.90***	-0.62*	0.20	6.55***	7.30***	-0.09	12.44***	13.58***
	(0.15)	(1.16)	(0.36)	(0.27)	(2.16)	(0.64)	(0.37)	(2.98)	(1.02)
FL$_{EAL}$	-0.01	-0.01*	-0.00**	-0.01*	-0.03**	-0.01***	-0.01	-0.02	-0.00
	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.02)	(0.01)
BM$_t$		0.01	0.28***		0.12	1.05***		0.02	-0.57**
		(0.29)	(0.09)		(0.54)	(0.16)		(0.72)	(0.25)
P$_t$		-0.43**	0.41***		-1.08***	-0.45***		-1.17**	-0.62***
		(0.21)	(0.07)		(0.40)	(0.12)		(0.52)	(0.18)
MC$_t$		-0.15	0.03		0.06	-0.20***		-0.73**	-1.12***
		(0.12)	(0.04)		(0.23)	(0.07)		(0.31)	(0.10)
TURN		-0.00	-0.75***		0.26	-0.25		2.38*	1.69***
		(0.47)	(0.15)		(0.88)	(0.26)		(1.22)	(0.42)
σ_m		-0.08***	-0.07***		-0.22***	-0.26***		-0.18**	-0.18***
		(0.03)	(0.01)		(0.05)	(0.02)		(0.07)	(0.03)
MOM		0.00	0.01***		0.00	0.00		0.00	-0.03***
		(0.00)	(0.00)		(0.01)	(0.00)		(0.01)	(0.00)
N	581	278	278	581	280	280	581	280	280
R^2	0.00	0.06		0.01	0.10		0.00	0.08	

Note: *p<0.1; **p<0.05; ***p<0.01

Table XXVIII. Flood risk for companies impacted by Flood: from columns (1) to (3) we provide regressions of the independent variables on CAR_{it1}, where in column (1) the indipendent variable is FL_{EAL}, in column (2) we include controls and in column (3) we include a robust estimation accounting for outliers. Similar applies for columns (4) to(6) which are a regression on CAR_{it10} and columns (7) to (9) on CAR_{it22}.

	Dependent variable: $CAR_{it\Delta}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
β_0	0.06	3.91***	1.59***	-0.01	6.64***	7.44***	-0.31	12.85***	13.88***
	(0.14)	(1.16)	(0.38)	(0.25)	(2.19)	(0.62)	(0.35)	(2.99)	(1.02)
$\text{FL}_{ins_{EAL}}$	0.00	-0.01	-0.01**	-0.00	-0.03	-0.02***	0.02	0.01	0.01
	(0.01)	(0.01)	(0.00)	(0.02)	(0.03)	(0.01)	(0.02)	(0.03)	(0.01)
BM_t		-0.06	0.25***		-0.07	1.10***		-0.19	-0.53**
		(0.29)	(0.09)		(0.54)	(0.15)		(0.72)	(0.24)
P_t		-0.36*	-0.11*		-0.88**	-0.39***		-1.05**	-0.68***
		(0.21)	(0.07)		(0.39)	(0.11)		(0.52)	(0.18)
MC_t		-0.20*	-0.02		-0.08	-0.26***		-0.88***	-1.12***
		(0.12)	(0.04)		(0.22)	(0.06)		(0.30)	(0.10)
TURN		0.06	-0.39**		0.44	-0.10		2.54**	1.39***
		(0.47)	(0.15)		(0.89)	(0.25)		(1.22)	(0.41)
σ_m		-0.08***	-0.07***		-0.23***	-0.27***		-0.19**	-0.18***
		(0.03)	(0.01)		(0.05)	(0.02)		(0.07)	(0.03)
MOM		0.00	0.00		0.00	0.01**		0.00	-0.02***
		(0.00)	(0.00)		(0.01)	(0.00)		(0.01)	(0.00)
N	581	278	278	581	280	280	581	280	280
R^2	0.00	0.05		0.00	0.08		0.00	0.08	
Note:									*p<0.1; **p<0.05; ***p<0.01

Table XXIX. Flood risk for companies impacted by Flood with historical insurance coverage: from columns (1) to (3) we provide regressions of the independent variables on CAR_{it1}, where in column (1) the indipendent variable is HB_{cr}, in column (2) we include controls and in column (3) we include a robust estimation accounting for outliers. Similar applies for columns (4) to(6) which are a regression on CAR_{it10} and columns (7) to (9) on CAR_{it22}.

	Dependent variable: $CAR_{it\Delta}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
β_0	-0.08	2.32*	0.22	0.11	4.65*	6.42***	-1.05*	6.59*	13.06***
	(0.23)	(1.38)	(0.42)	(0.43)	(2.64)	(0.69)	(0.60)	(3.50)	(1.21)
EHB	0.01	0.01**	0.00	0.00	0.01	0.00	0.02*	0.05***	0.04***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.02)	(0.01)
FL_{EAL}	-0.00	-0.01	0.00	-0.02*	-0.04**	-0.04***	-0.03*	-0.03	-0.04***
	(0.01)	(0.01)	(0.00)	(0.01)	(0.02)	(0.01)	(0.02)	(0.03)	(0.01)
$\text{FL}_{EAL} : EHB$	-0.00	0.00	-0.00***	0.00	0.00	0.00***	0.00**	0.00	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
BM_t		0.14	0.18**		0.32	1.33***		0.44	0.57**
		(0.30)	(0.09)		(0.56)	(0.15)		(0.72)	(0.25)
P_t		-0.40*	0.25***		-1.04***	-0.46***		-1.05**	-1.06***
		(0.21)	(0.06)		(0.40)	(0.10)		(0.52)	(0.18)
MC_t		-0.04	0.04		0.19	-0.13**		-0.33	-0.68***
		(0.13)	(0.04)		(0.25)	(0.06)		(0.33)	(0.11)
TURN		-0.31	-0.86***		-0.07	-0.39		1.27	0.09
		(0.49)	(0.15)		(0.93)	(0.24)		(1.26)	(0.44)
σ_m		-0.07**	-0.09***		-0.20***	-0.24***		-0.15**	-0.32***
		(0.03)	(0.01)		(0.06)	(0.01)		(0.07)	(0.03)
MOM		0.00	0.00***		0.00	0.00*		0.00	-0.02***
		(0.00)	(0.00)		(0.01)	(0.00)		(0.01)	(0.00)
N	581	278	278	581	280	280	581	280	280
R^2	0.01	0.08		0.01	0.11		0.02	0.12	
Note:									*p<0.1; **p<0.05; ***p<0.01

Table XXX. Flood risk and EHB regressions for companies impacted by Floods: from columns (1) to (3) we provide regressions of the independent variables on CAR_{it1}, where in column (1) the indipendent variable is EHB, in column (2) we include controls and in column (3) we include a robust estimation accounting for outliers. Similar applies for columns (4) to(6) which are a regression on CAR_{it10} and columns (7) to (9) on CAR_{it22}.

	Dependent variable: $CAR_{it\Delta}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
β_0	-0.26	2.20	0.74*	-0.29	4.07	6.58***	-1.43***	6.16*	12.90***
	(0.21)	(1.38)	(0.45)	(0.39)	(2.65)	(0.74)	(0.54)	(3.48)	(1.19)
EHB	0.01*	0.02**	-0.00	0.01	0.02	0.01	0.03***	0.06***	0.04***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.02)	(0.01)
$\text{FL}_{ins_{EAL}}$	0.02	-0.00	-0.01	-0.01	-0.06	-0.08***	-0.00	0.00	-0.00
	(0.02)	(0.03)	(0.01)	(0.03)	(0.06)	(0.02)	(0.05)	(0.07)	(0.02)
$\text{FL}_{ins_{EAL}} : EHB$	-0.00	-0.00	-0.00	0.00	0.00	0.00***	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
BM_t		0.08	0.06		0.24	1.50***		0.29	0.65**
		(0.31)	(0.10)		(0.58)	(0.16)		(0.74)	(0.25)
P_t		-0.35*	0.07		-0.85**	-0.40***		-0.98*	-1.03***
		(0.21)	(0.07)		(0.39)	(0.11)		(0.51)	(0.17)
MC_t		-0.08	0.02		0.11	-0.16**		-0.38	-0.76***
		(0.13)	(0.04)		(0.24)	(0.07)		(0.32)	(0.11)
TURN		-0.29	-0.68***		-0.02	-0.28		1.19	2.63***
		(0.49)	(0.16)		(0.94)	(0.26)		(1.25)	(0.43)
σ_m		-0.07**	-0.07***		-0.20***	-0.26***		-0.15**	-0.33***
		(0.03)	(0.01)		(0.06)	(0.02)		(0.07)	(0.03)
MOM		0.00	0.00*		0.00	0.01***		0.00	-0.02***
		(0.00)	(0.00)		(0.01)	(0.00)		(0.01)	(0.00)
N	581	278	278	581	280	280	581	280	280
R^2	0.01	0.07		0.00	0.09		0.02	0.12	

Note: *p<0.1; **p<0.05; ***p<0.01

Table XXXI. Flood risk and EHB regressions for companies impacted by Floods with historical protection: From columns (1) to (3) we provide regressions of the independent variables on CAR_{it1}, where in column (1) the indipendent variable is EHB, in column (2) we include controls and in column (3) we include a robust estimation accounting for outliers. Similar applies for columns (4) to(6) which are a regression on CAR_{it10} and columns (7) to (9) on CAR_{it22}.