Local Ownership and Price Discovery around Extreme Weather Events[1]

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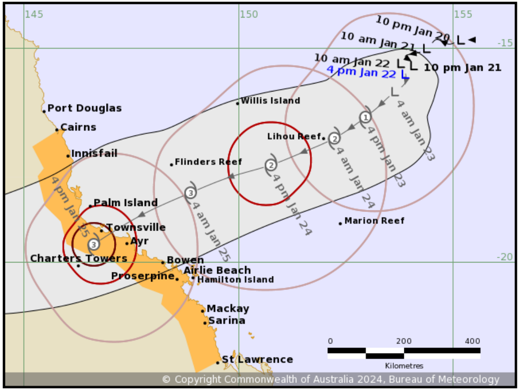
The context and setting of this study

- We conjecture that **local institutional investors have more knowledge on local companies** and can better price risks (Coval and Moskowitz, 2001)
- We use a **convenient identification strategy** as we test the impact of ownership on price discovery exploiting the exogeneous impact of **extreme weather events**
- **Extreme weather events** come with **uncertainty** about **occurrence and impact** (Kruttli et al., 2023)
- A good understanding of the impact of extreme weather events requires **specific/local knowledge on facilities' locations and their vulnerabilities**
- If local institutional owners are indeed better informed then:
  - extreme weather events lead to a **lower surprise for those companies which are more owned by local institutional investors**
  - local investors **lose this informational advantage with a greater informational distance**

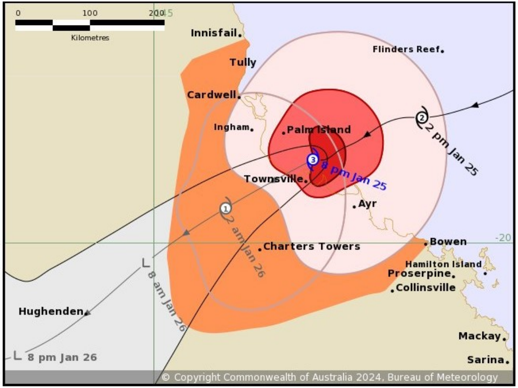
Uncertainty and market segmentation

- Investment uncertainty makes investors **prone to market segmentation as...**
  1. ... they invest in assets that are "closer" to them correctly picking the outperforming ones (Van Nieuwerburgh and Veldkamp, 2009; Coval and Moskowitz, 2001)
  2. ... they prefer local companies compared to foreign ones for the same level of climate risk (Boermans and Galema, 2023)
- **Uncertainty** related to extreme weather events **affects firms' and therefore investors' returns more strongly in segmented markets** if there is (Kruttli et al., 2023):
  1. a higher **probability of the company's facilities being impacted**
  2. a higher **uncertainty of the expected damage conditional on the company's facilities being hit**
  3. a lower **share of local ownership**

Storms: longer forecast horizon and higher forecast uncertainty

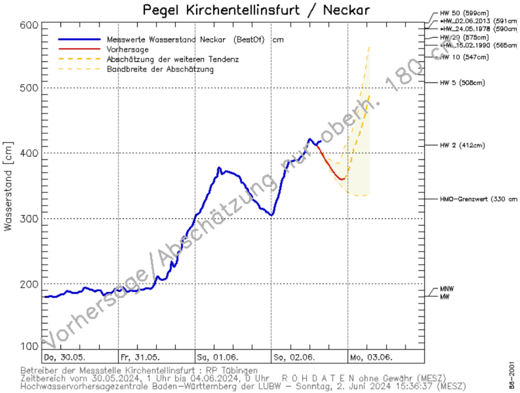


(a) Storm Kyrill: January 21 2024

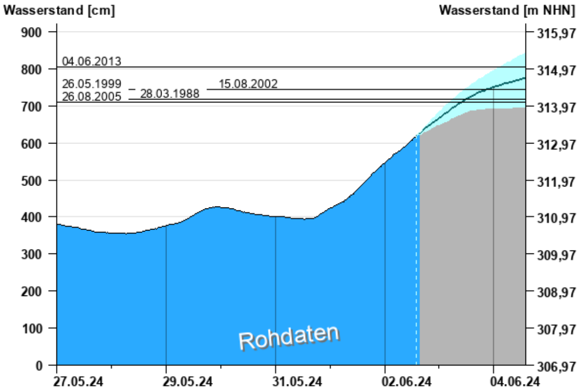


(b) Storm Kyrill: January 25 2024

Floods: shorter forecast horizon and lower forecast uncertainty



(a) Flood Neckar: June 2 2024



(b) Flood Donau: June 2 2024

Research question

- **Are local institutional investors better informed about the exposures of local companies to extreme weather events?**
- Potential mechanisms:
  1. **Local news and knowledge** give local investors a better understanding of specific assets' risks
  2. Extreme weather events may trigger **different investors' reactions to uncertainty**
- Contribution:
  1. **Interaction of local ownership with informational distance exploiting extreme weather events**. Where informational distance is proxied using the physical distance between the headquarters and a facility.
  2. **Connecting innovative data sources with fuzzy string matching and spatial identification** of the impacts of extreme weather events using geographical information on facilities' and events

Hypotheses:

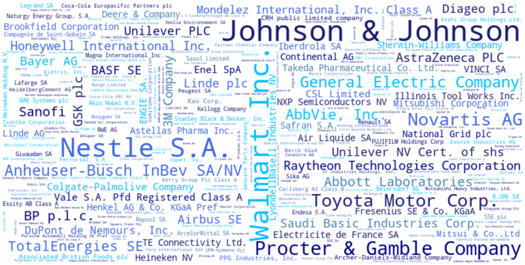
- $H_1 \Rightarrow$ Extreme weather events with **a long forecasting horizon and a high forecast uncertainty trigger a more negative surprise from investors** (Kruttli et al., 2023; Merz et al., 2020)
- $H_2 \Rightarrow$ The higher the degree of **local institutional ownership** in a company before an event, the **lower the negative surprise** at event occurrence. (Kruttli et al., 2023)
- We then further **test that the better knowledge of local institutional ownership is related to informational distance** by investigating two potential mechanisms:
  1. H_3: The **larger the local investors' base the lower the negative surprise for securities with a higher physical risk exposures**, as this is already priced in by local investors (Pellegrino et al., 2022; Coval and Moskowitz, 2001)
  2. H_4: A **higher distance** between facilities and headquarters **is an informational disadvantage for local investors**, the larger the distance the stronger the negative price reaction driven by local investors (Kruttli et al., 2023; Pellegrino et al., 2022)

Empirical setting of the event study

- We study cumulative average abnormal stock returns (CAAR) of impacted companies around storms and floods event dates. We identify impacted companies by means of:
  1. A **spatial** identification Go to spatial identification:
     - Location and ownership of firms' production facilities (Kruttli et al., 2023; Huynh and Xia, 2021)
     - Location, timing and area of floods (Brakenridge, 2021), wind storms (Copernicus)
  2. A **time** identification Go to Event design:
     - Companies' and facilities' ownership over time
     - We set the estimation period to 90 days, as such between Kruttli et al. (2023) and Blanco et al. (2024) and ensure that is not biased by extreme weather events of the same type.
  3. Accounting for **market microstructure** effects and trading:
     - At least 10% of the outstanding shares is free float
     - The stock price was traded above € 5 in the estimation period
     - We exclude companies related to the broad financial sector (also insurance companies)

The sample

- Our sample has 832 unique ISINs linked to 4,162 facilities, of which around 353 ISINs and 1,377 facilities are impacted at least once from 2014 to 2021.
- The impacted **sectors are materially relevant for physical risk analysis** as most of the impacted companies are in the food, manufacturing and utility industries



Methodology: event study, security ownership and physical risk

- The event study methodology follows MacKinlay (1997) and Barrot and Sauvagnat (2016). We compute:
  1. Abnormal returns with several factor models (Market, 3F, 4F, 5F) ▸ Abnormal Return Methodology
  2. Variances that account for event induced variance ▸ Robust Variance
- Local security ownership is the % of institutional owners based in the same country of the security at time $t-1$ ▸ (Coeurdacier and Rey, 2013)
- Companies' exposure to weather events follows the methodology from ECB (2023) and we compute the Expected Annual loss (*EAL*) at facility level ▸ EAL Methodology

Case studies: Ciara and the summer floods in 2021

	CAAR							
	Windstorm Ciara 2020				Summer floods July 2021			
	Mkt	*3F*	*4F*	*5F*	*Mkt*	*3F*	*4F*	*5F*
(-5,-2:-1)	-0.81***	-0.85***	-0.83***	-0.78***	0.73***	0.6**	0.45*	0.37
	(0.14)	(0.14)	(0.14)	(0.14)	(0.21)	(0.25)	(0.25)	(0.24)
(0:10)	-2.91***	-2.72***	-2.72***	-2.79***	0.63***	0.29	0.13	-0.16
	(0.27)	(0.29)	(0.29)	(0.32)	(0.24)	(0.27)	(0.29)	(0.29)
(11:22)	-1.38***	-1.71***	-1.37**	-1.66***	-0.61**	-0.74**	-1.54***	-2.16***
	(0.49)	(0.48)	(0.56)	(0.5)	(0.31)	(0.32)	(0.41)	(0.38)
N	39	39	39	39	9	9	9	9

Note: -5 and -2 are the dates where the event study begins for storms and floods respectively

Annual reports of the companies impacted in the case studies

For wind **storm Ciara**:

- *"Aperam's manufacturing plant have experienced and may in future experience, **plants shutdowns or periods of reduced production as a result of** such process failures, or other events such as **natural disasters [...] or extreme weather events**"* Aperam SA (2020)
- *"SCA's forest land is spread across large areas of Northern Sweden, which means that **forest fires and storms can usually only impact a minor part of the forest portfolio. The forest is therefore not insured**."* SCA (2020)

For the **floods in 2021**:

- *"VINCI is **highly exposed to the acute physical risks** associated with climate change. Extreme weather events can negatively impact the Group's activities in different ways, such as **damage to worksites or flooded runways** ..."* Vinci SA (2022)
- *"A major event in the Recycling Business ([...] **prolonged flooding**, etc.) could lead to a **prolonged breakdown in the logistic chain**. Major accident [...] or a natural disaster (earthquake, **flood**, etc) **interrupting operations**."* Derichenbourg (2022)

Regression analysis: The variables

- $CAR_{model,it}$: **Cumulative abnormal returns during the event window**, with a daily frequency, computed with different estimation models.
- $LO_{i,t-1}$: **Local institutional ownership** in the quarter preceding the event date as a share of total institutional ownership.
- EAL_i: **Expected annual loss at a company level for the specific event type as a share of all potentially damageable assets**. The company EAL_i is an unweighted average over all facilities.
- *Distance*: is defined as **distance in kilometers**.

Sample summary statistics

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

H1: Windstorms bear uncertainty leading to negative surprises

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

Note: -5 and -2 are the dates where the event study begins for storms and floods respectively

H2: Local equity ownership reduces negative windstorms impact

	$CAR_{t,Mkt}$					
	WIND			FLOOD		
	(1)	(2)	(3)	(1)	(2)	(3)
β_0	0.0064	-0.0008	0.1136	0.2610	0.3110	0.1605
	(0.2538)	(0.2565)	(0.2641)	(0.2362)	(0.2250)	(0.2543)
$LO_{(t-1)}$	0.0131***	0.0060	0.0118***	0.0026	0.0014	0.0105***
	(0.0021)	(0.0039)	(0.0043)	(0.0027)	(0.0031)	(0.0035)
$Post$	-2.6585***	-2.0402***	-3.0545***	-0.6898**	-0.7927***	-0.8900***
	(0.3216)	(0.3501)	(0.3317)	(0.2850)	(0.2870)	(0.3046)
$LO_{(t-1)} \cdot Post$	0.0226***	0.0139***	0.0468***	0.0035	0.0062	0.0056
	(0.0030)	(0.0050)	(0.0055)	(0.0038)	(0.0044)	(0.0047)
N	5593	5593	5593	14022	14022	14022
R^2	0.0322	0.0514	0.0353	0.0014	0.0020	0.0048
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

H3: Higher exposure leads to a stronger negative surprise

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

H4: Informed investors react less positively with higher distance

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

(Preliminary) Conclusions

- Ownership matters for price discovery: **stock prices of companies with more local institutional investors are less impacted by the occurrence of extreme weather events**
- This is specially the case for wind storms because they come with higher uncertainty of impact and forecast.
- **The negative impact of extreme weather events on stock prices is larger, the greater the informational distance**.
- Results are robust also after excluding the US, year 2020 and persist over the different estimation methods.
- Extensions ongoing on expected event loss at a facility level, distance owners with facility

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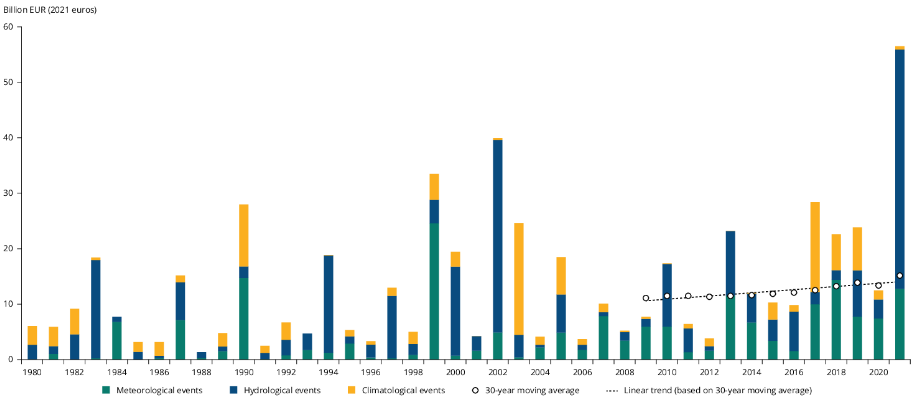
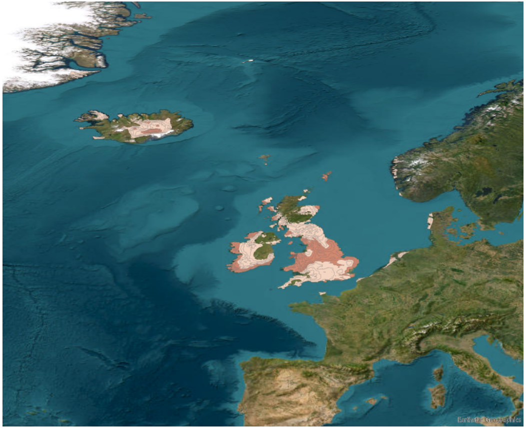
Weather disasters affected Europe in the last 20 years



Source European Environment Agency: Economic losses from climate-related extremes in Europe (8th EAP)

Spatial identification: windstorm in 2020, floods in 2021



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

(b) Floods (13 - 15 Jul 2021)

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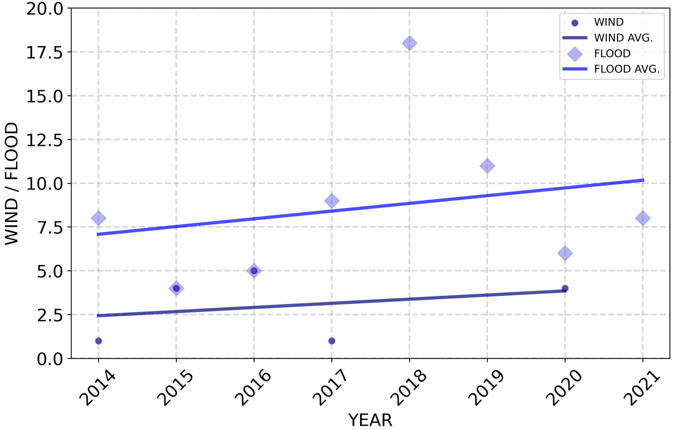
References

Overall distributions of weather events over time and type



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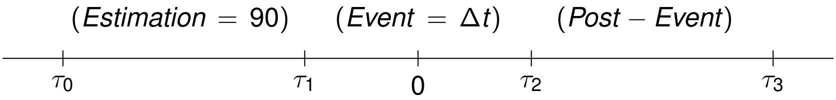
Event Study: Time identification

- A company is in the event only if there are no similar hazards in the estimation window



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Appendix - Ownership Definitions

- SUBS: A is subsidiary of B if A has any stake in B with percentage of Ownership
- COMP: Target company linking
- ISH: shareholder at first level (e.g. immediate shareholder)
- DUO: domestic ultimate owner with a definition min 50% ownership stake[2]
- GUO: global ultimate owner with a definition min 50% ownership stake

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[2] only with owner (shareholder) types B, C, A and F (e.g., banks, trade industry organisation, insurance and financial)

Event study: Abnormal returns

We define the abnormal return for company *i* around event *e* at time *t* as follows

$$AR_{i,e,t} = R_{i,e,t} - E[R_{i,e,t}|X_{i,e,t}]$$

Where $E[R_{i,e,t}|X_{i,e,t}]$ is computed with different models Mkt, $3F$, $4F$, $5F$ for companies $i = (1, .., N)$ and events $e = (1, .., M)$ for a specific hazard type

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

$$CAAR_t = \frac{1}{N}\frac{1}{M}\sum_{i=1}^{N}\sum_{e=1}^{M} CAR_{i,e,t}$$

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Event study: Significance Tests

The cross sectional test

$$t = \sqrt{N}\frac{CAAR}{S_{CAAR}} \text{ with } S^2_{CAAR} = \frac{1}{N-1}\sum_{i=1}^{N}(CAR_i - CAAR)^2$$

and the cross sectional test under event-induced variance (Boehmer et al., 1991)

$$t = \sqrt{N}\frac{\overline{SCAR}}{S_{\overline{SCAR}}}$$

where

$$\overline{SCAR} = \frac{1}{N}\sum_{i=1}^{N} SCAR_i \text{ and } S^2_{\overline{SCAR}} = \frac{1}{N-1}\sum_{i=1}^{N}(SCAR_i - \overline{SCAR})^2$$

with $SCAR_i = \frac{CAR_i}{S_{CAR_i}}$ denoting the forecast-error-corrected standard deviation. Return to presentation

Stock and facility Ownership

The share of home institutional investors that invest in company *i* follows Coeurdacier and Rey (2013)

$$LO_{i,t} = 1 - \left(\frac{\%\ of\ foreign\ IO\ in\ company\ i\ at\ time\ t}{\%\ IO\ in\ company\ i\ at\ time\ t} \right)$$

- We define facilities' ownership as:
  - **Abroad**: Facility's country $\neq$ Headquarters' country
  - **Home**: Facility's country = Headquarters' country

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Expected annual loss (EAL)

We compute the *EAL* for every facility held by a company with at least a 50% ownership structure in the ownership chain. The *EAL*'s formula follows Antofie et al. (2020):

$$EAL = \sum_{i=T_1}^{T_n} (p_i L_i). \tag{1}$$

Where:

- p_i is the probability of occurrence for a single event in a given return period,
- L_i is the loss faced by the investor,
- We account for insurance by including the uninsured percentage of losses by event on a country level and multiply with the company level *EAL*. Return to presentation

EAL an example

For a wind speed between 30 km/h and 35 km/h for wind storms, we take the damage ratio associated with this intensity bucket and calculate the *EAL* as a weighted average over all intensity buckets

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}.

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

We express *EAL* for all events in one year as follows where L_i is the damage ratio

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