

Natural Disasters, Reshoring Dynamics and Automation

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EEA Congress 2025

- Recent theoretical studies investigate the relationship between **reshoring** of economic activities, **domestic employment**, and **automation** (Krenz et al., 2021; Artuc et al., 2023; Faber et al., 2023).
- From an **empirical** standpoint, this is a **challenging** question to address.
 - Need to disentangle these processes from the broader internationalisation strategies pursued by MNEs.
- **Solution**: link individual reshoring decisions to shocks that are **exogenous** in nature and **unpredictable** in timing.
- **What we do**: leverage the **exposure of foreign subsidiaries to local natural disasters**.

Automation and skill demand

- Robot adoption has an **ambiguous effects** on workers (Acemoglu and Restrepo, 2020; Aghion et al., 2020):
(-) **displacement effect** (+) **productivity effect** (+) **reinstatement effect**
- A recent empirical literature has tried to test these different mechanisms using firm-level data.
(Acemoglu, Lelarge, et al., 2020; Acemoglu, Koster, et al., 2023; Humlum, 2022; Dixon et al., 2021; Koch et al., 2021; Cheng et al., 2019; Dinlersoz and Wolf, 2023)
- The causal identification generally relies on technological shocks or firm-level measures of exposure.
(Bessen et al., 2020; Aghion et al., 2020; Acemoglu, Koster, et al., 2023; Bonfiglioli, Crino, et al., 2024)

Reshoring and automation

- Increasing **efficiency** of automation technologies and rising trade costs lead to a **relocation** of previously offshored production **back to the home country** (Krenz et al., 2021; Bonfiglioli, Crinò, et al., 2022).
 - Foreign automation affects foreign-owned firms in Brazil (Stemmler, 2019) and LLMs in Mexico (Faber, 2020).
 - Country-level uncertainty shocks foster reshoring, but only in highly robotised industries (Faber et al., 2023)
- However, the productivity gains recorded by the robot adopters raise the demand for foreign inputs and could **offset the displacement effects** in destination countries (Artuc et al., 2023).
 - Positive impacts of robot intensity in US (Hallward-Driemeier and Nayyar, 2019) and Spain (Stapleton and Webb, 2020) on imports sourced from (or FDI growth to) lower-income countries.

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This paper

Research questions

- Do natural disasters foster the reshoring of economic activities?
- Do these shocks affect skill demand and automation in parent firms?

What we do

- Combine geolocated data on natural shocks and foreign affiliates with firm-, product- and individual-level data for France
- Assess how these idiosyncratic shocks affect individual subsidiaries and the overall business group.
- Analyse how the exposure to foreign shocks affect parent firm's technology and domestic skill composition

Results

- Reshoring decisions driven by exogenous shocks may not lead to widespread job creation but can instead reinforce a process of skill-biased technological change and increase wage inequalities.

Mechanisms: sunk costs and uncertainty

- **Background:** Advancing automation technologies and steady or rising trade costs
- Firms choose between investing in cheap labour abroad or automation at home (fixed costs)
 - Offshoring firms face **sunk costs** (search and negotiation costs, physical assets)
 - Sunk costs increase in the **minimum efficiency level of domestic technologies** that makes it profitable to reshore → relative **stickiness** of the production process
- Unexpected shocks can hit one or more affiliates:
 - damaging assets
 - disrupting the local value chain
 - changing in other ways the local business environment.
- **Mechanisms:** Idiosyncratic shocks to foreign affiliates force the parent firm to:
 1. further invest in the area to keep producing there.
 - **decrease in the opportunity cost** to reshore and invest in automation
 2. reassess the overall **risk exposure** of the multinational BG (including unaffected subsidiaries).
 - if home country perceived as safer than other location, this can also lead to reshoring dynamics

1. First paper that provides **firm-level evidence** about the relationship between reshoring and automation.
2. We produce a **panel geolocated dataset** which allows us to study the **firm-level exposure to subnational foreign shocks** – previous firm-level literature mostly exploited country-level shocks
3. Focus on a specific channel, namely the **reduction in opportunity cost** for a domestic investment in automation

Data

- We exploit four main data sources:

1. Subnational data on **natural disasters**

- Coverage: World
- Period: 1980-2022

2. Firm-level data on **global ownership networks**

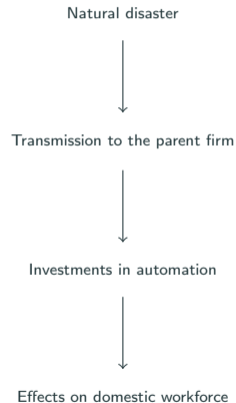
- Coverage: World
- Period: 2010-2021

3. Firm-level **balance sheet** and **customs data**

- Coverage: France
- Period: 1994-2022

4. **Matched employer-employee** data

- Coverage: France
- Period: 1994-2022



- **Natural disasters**

- Data on natural disasters are retrieved from EMDAT (24,500 natural disasters from 1900 to present)
- Info on number of people affected, fatalities and damages.
- We **map** disaster-level data to a regional-level dataset: (Rosvold and Buhaug, 2020) + own geocoding
- **Natural disasters assigned to 3,600 GADM Administrative Units**

▶ Identification of relevant disasters

▶ Disaster Proxies

- **Ownership networks**

- Data on global ownership and financial accounts of foreign subsidiaries retrieved from BVD Orbis
- We **geolocate** each subsidiary and assign it to one of the 3,500 GADM areas.
- We adopt an **iterative process** which progressively identifies **ownership linkages** by:
 - (1) Direct control
 - (2) Transitivity
 - (3) Consolidation of voting rights
- We map over **6,000,000** affiliates for the period period 2010-2021.

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- **FARE** (Fichier Approché des Résultats d'Esane)
 - Balance sheet information on the quasi-universe of French private companies
 - Information on output, value added, employment + full breakdown of investments by asset type.
 - We exploit it to construct the **proxy for 'machinery'**
→ investments in 'Machinery, equipment and tools'
- **Customs data**
 - Data retrieved from an administrative dataset produced by French Customs.
 - Firm-level data on imports and exports by partner country and 8-digit CN product.
→ 8,000 product varieties from/to 161 countries over the period 1994-2021.
 - The dataset is used to construct a **proxy for automation technologies**, based on the value of imported automation products (as in Aghion et al., 2020 and Bonfiglioli, Crino, et al., 2024).



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▶ Descriptives

▶ Automation proxy

- **DADS** (Déclaration Annuelle de Données Sociales)
 - Coverage: approx. 30,000,000 workers per year (almost 100% of private sector workers in France).
 - Worker-Level Information: gross annual income, total paid hours, employment start/end dates, status (full-time/part-time), specific occupation (4-digit level), home municipality, gender, birth year,...
 - **Intense data cleaning** process: we integrate info on **task content** and data from different sources
 - We construct a **pseudo-panel** dataset, following the method outlined in [Babet et al. \(2022\)](#).
- **O*NET** (US Occupational Information Network)
 - Conversion to 4-digit PCS occupations using weights constructed on the basis of the European Labour Force Survey (LFS).
 - Used to classify workers in **routine** and **non-routine** occupational categories.

Divestment decisions and business group restructuring

- Our baseline specification models the divestment propensity of firms as a function of the exposure to a local shock that affected the region where the subsidiary is located in $t - 1$.

$$D_{ijkt} = X'_{i,t-1}\beta_1 + \beta_2 ND_{it-1} + \gamma_i + \phi_{c_i,k_i,t} + \rho_{jt} + \varepsilon_{ijkt} \quad (1)$$

- D_{ijvt} : dummy that equals one if the subsidiary is divested in time t
 - ND_{it-1} : dummy switching on from the year after the host region c_i experiences an adverse event
 - $X'_{i,t-1}$: vector of time varying firm-level characteristics recorded in $t - 1$
 - $\gamma_i, \phi_{c_i,k_i,t}, \rho_{jt}$: subsidiary, destination country-industry-year and parent firm-year fixed effects
- Robustness:
 - Breakdown by disaster type
 - Disaster intensity
 - Low-risk regions

- How does the whole business group react to the shock?
- Business group-level specification:

$$\Delta Naff_{jct} = X'_{j,t-1}\beta_1 + \beta_2 \max_{i \in j} \{ND_{ijt-1}\} + \gamma_j + \lambda_{ct} + \varepsilon_{jct} \quad (2)$$

- $\Delta Naff_{jct}$: change in the number of foreign affiliates
 - $\max_{i \in j} \{ND_{ijt}\}$: dummy switching on the year after one or more affiliates are hit by a natural disaster
 - $X'_{j,t-1}$: vector of business group characteristics
 - γ_j, λ_{ct} : business group and parent country-year fixed effects
- Robustness:
 - Event study
 - Low-risk regions
 - Trade in intermediates

Subsidiary-level analysis (1)

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.: Divestment						
Natural Disaster	0.0556*** (0.0206)	0.0364*** (0.0112)	0.0233*** (0.00713)	0.0236*** (0.00750)	0.0243*** (0.00737)	0.0413*** (0.00828)
Observations	5,889,828	5,146,797	4,131,607	4,131,607	4,000,045	4,126,908
R-squared	0.336	0.375	0.672	0.672	0.670	0.681
Subsidiary-level controls	-	-	-	✓	✓	✓
Bilateral controls	-	-	-	-	✓	-
Subsidiary FE	✓	✓	✓	✓	✓	✓
Parent country×year FE	✓	✓	-	-	-	-
Year×Macroregion×Industry FE	-	✓	✓	✓	✓	-
Parent firm×year FE	-	-	✓	✓	✓	✓
Destination Country×Industry×Year FE	-	-	-	-	-	✓

- Natural disaster → 2/4% increase in the likelihood of divestment

▶ Disaster intensity

▶ Low-risk regions

▶ Breakdown by shock type

Subsidiary-level analysis (2)

Dep. Var.: Divestment	(1)	(2)	(3)	(4)	(5)	(6)
Natural disaster	0.0602*** (0.00901)	0.0410*** (0.00810)	0.0392*** (0.0086)		0.0268*** (0.00824)	0.0980*** (0.0182)
Natural disaster×Parent historic risk exposure	-0.0233*** (0.00800)					
Natural disaster×logDistance		0.0119*** (0.00302)				
Natural disaster×Routine task intensity			0.0091*** (0.0017)			
Natural disaster×1st Layer				-0.00194 (0.00829)		
Natural disaster×2nd Layer				0.0564*** (0.00358)		
Natural disaster×3rd+ Layer				0.0789*** (0.00476)		
Observations	3,992,363	3,992,363	3,986,700	3,992,363	3,530,086	395,433
R-squared	0.679	0.679	0.679	0.679	0.676	0.727
Subsidiary FE	✓	✓	✓	✓	✓	✓
Destination Country×Industry×Year FE	✓	✓	✓	✓	✓	✓
Parent firm×year FE	✓	✓	✓	✓	✓	✓
Income Group	All	All	All	All	HI	MLI

- Firms more likely to be divested **the longer the geographical and 'ownership' distance** from the parent firm, and **the lower the historical risk exposure** of the BG

Business group-level analysis

	(1)	(2)	(3)	(4)	(5)
Dep var.: Δ Affiliates					
Natural Disasters	-0.109*** (0.0121)	-0.106*** (0.00963)	-0.144*** (0.0239)	-0.122*** (0.0207)	-0.114*** (0.0199)
Observations	2,190,298	2,190,170	269,266	552,143	65,027
R-squared	0.159	0.162	0.175	0.198	0.140
BG FE	✓	✓	✓	✓	✓
Year FE	✓	-	-	-	-
Parent country \times Year FE	-	✓	✓	✓	✓
Parent country	All	All	All	All	France
BG size	All	All	≥ 5	All	All
Home country risk level	All	All	All	Below average	All

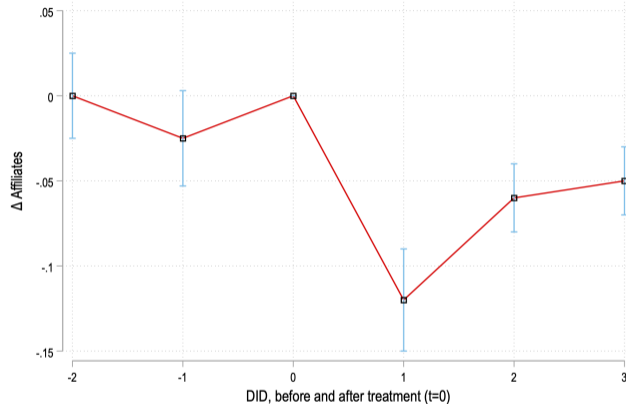
- Natural disaster \rightarrow 10% standard deviation decrease in the year-to-year growth rate of the BG
- Not all divested subsidiaries are replaced with other foreign investments

▶ Low-risk regions only

▶ Breakdown by layer and BG type

▶ Trade in intermediates

Business group-level Event Study



- **Not all** divested subsidiaries are **replaced** with other foreign investments
- **No evidence** of short-term **adjustment**

▶ Low-risk regions only

▶ Breakdown by layer and BG type

▶ Trade in intermediates

Skill composition and automation of parent firms

- We develop a measure of the **parent firm's exposure to local shocks**, by weighting the treatment variable by the share of the overall BG's foreign employment in pre-sample period:

$$\overline{WND}_{jt} = \sum_i ND_{ijt} \frac{L_{ijt-n}}{L_{jt-n}}$$

- The specification takes the following form:

$$\ln Y_{jt} = X_{jt}'\beta_1 + \beta_2 \overline{WND}_{j,t-1} + \gamma_j + \psi_{kt} + e_{jt} \quad (3)$$

- Y_{jt} : outcome recorded by firm j , in time t
- X_{jt} : vector of time-variant firm j characteristics
- γ_j, ψ_{kt} : firm and industry-year fixed effects.

► Controlling for non-random exposure (Borusyak & Hull, 2023)

Parent firm-level analysis

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$$\overline{WND}_{jt} = \sum_i ND_{ijt} \frac{L_{ijt-n}}{L_{jt-n}}$$

- The specification takes the following form:

$$\ln Y_{jt} = X'_{jt}\beta_1 + \beta_2 \overline{WND}_{j,t-1} + \gamma_j + \psi_{kt} + e_{jt} \quad (3)$$

- Y_{jt} : outcome recorded by firm j , in time t
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▶ Controlling for non-random exposure (Borusyak & Hull, 2023)

- To isolate the effect of local shocks on individual workers, we estimate a worker-level specification:

$$\ln w_{\nu jt} = \beta_1 X_{\nu t} + \beta_2 X_{jt} + \beta_3 \overline{WND}_{j,t-1} + \gamma_{\nu} + \lambda_j + \psi_{kt} + e_{\nu jt} \quad (4)$$

- $w_{\nu jt}$: hourly wage
- X'_{jt} : vector of firm-level characteristics
- X'_{it} : vector of worker-level characteristics
- $\gamma_i, \lambda_j, \psi_{kt}$, are firm, worker and industry-year fixed effects.

▶ Controlling for non-random exposure (Borusyak & Hull, 2023)

Parent firm-level outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	In Employment	In Employment	In Intern. imports	In Intern. imports	In Machinery	In Machinery
Disaster exposure	0.00373 (0.00245)	0.00515** (0.0025)	-0.0264* (0.0135)	-0.0309** (0.0137)	0.0515** (0.0227)	0.0589** (0.0230)
Observations	43,983	43,967	54,588	54,581	54,044	55,036
R-squared	0.958	0.959	0.872	0.877	0.777	0.779
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Industry×Year FE	-	✓	-	✓	-	✓

- Shock affecting all foreign affiliates associated with:
 - 0.5% increase in employment
 - 3% decrease in trade in intermediates in the same industry ('narrow offshoring')
 - 6% increase in investment in machinery

▶ Controlling for non-random exposure

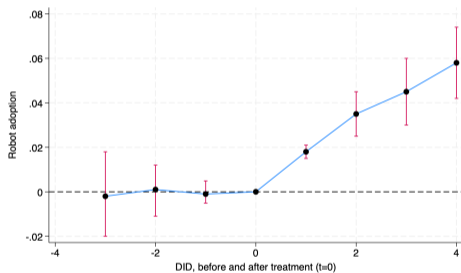
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	(1)	(2)	(3)	(4)	(5)	(6)
	In Employment	In Employment	In Intern. imports	In Intern. imports	In Machinery	In Machinery
Automation-intensive sectors						
Disaster exposure	0.00511 (0.00324)	0.00663** (0.00334)	-0.00589 (0.0212)	-0.00661 (0.0215)	0.0709** (0.0302)	0.0785** (0.0309)
Observations	25,449	25,483	28,145	28,138	28,101	28,093
R-squared	0.965	0.965	0.863	0.868	0.729	0.731
Other sectors						
Disaster exposure	0.002 (0.00373)	0.0032 (0.00362)	-0.0539*** (0.0132)	-0.0639*** (0.0137)	0.0231 (0.0347)	0.0281 (0.0344)
Observations	18,443	18,443	26,339	26,339	26,889	26,889
R-squared	0.949	0.951	0.882	0.887	0.774	0.775
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Industry×Year FE	-	✓	-	✓	-	✓

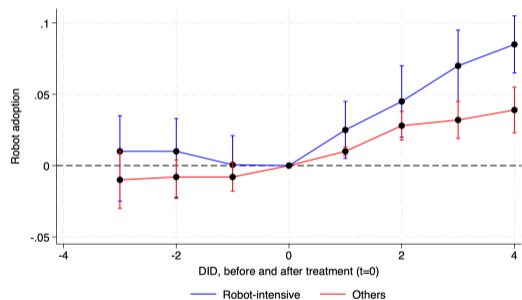
- **Positive** effect on **employment and machinery** concentrated **automation-intensive** industries
- **Negative** effect on total trade in **intermediates** concentrated in **non-automation intensive** industries

Figure 1: Robot adoption - event study
(estimator developed by De Chaisemartin and d'Haultfoeuille (2024))

(a) All manufacturing



(b) Breakdown by robot intensity



- Affected firms in **automation-intensive industries** are **more likely to become robot adopters**
- No significant effect in other industries

Worker-level analysis (1)

Dep var.	Hourly Wage					
	All manufacturing		Robot-intensive industries		Other industries	
	(1)	(2)	(3)	(4)	(5)	(6)
Natural disasters	0.0596** (0.025)	0.0668** (0.0261)	0.0706** (0.029)	0.0796** (0.0305)	0.0131 (0.0141)	0.0163 (0.0144)
Routine task		-0.0177*** (0.0024)		-0.0169*** (0.003)		-0.0186*** (0.00388)
Natural disasters x Routine task intensity		-0.0281*** (0.0096)		-0.0332*** (0.009)		-0.0175* (0.0101)
Observations	1,597,334	1,597,334	1,144,855	1,144,855	447,330	447,330
R-squared	0.906	0.908	0.901	0.903	0.922	0.922
Worker FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Year x industry FE	✓	✓	✓	✓	✓	✓

- Shock to foreign affiliates → 6% increase in wages. Effect concentrated in automation-intensive industries.

▶ Controlling for non-random exposure

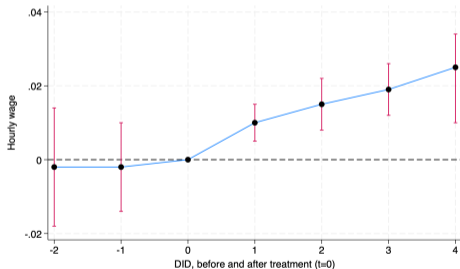
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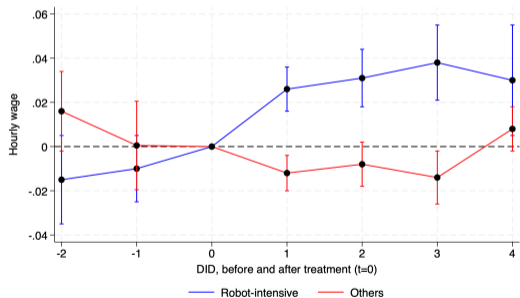
- Shock to foreign affiliates → 6% increase in wages. Effect concentrated in automation-intensive industries.
- The magnitude is reduced by half for workers in routine task-intensive occupations

Figure 2: Effect on wages - event study
(estimator developed by [De Chaisemartin and d'Haultfoeuille \(2024\)](#))

(a) All manufacturing



(b) Breakdown by robot intensity



Conclusions

- **Natural disasters foster the divestment of foreign affiliates**
 - Effect more pronounced when the subsidiary is located at **lower layers** of the BG, performs **routine-intensive** tasks and the BG is **more risk-averse**
- **Natural disasters affect technology and skill composition of parent firms**
 - **Robot-intensive sectors:** (+) investment in **automation** technologies
 - **Other sectors:** (-) intra-industry-trade in **intermediates**
 - **Positive wage effects** more pronounced for **non-routine** intensive occupations
- **Policy implications**
 - Need to account for **efficiency of emerging technologies** in each sector to assess the consequences of shocks to foreign activities
 - Policies promoting reshoring decisions need to be combined with **labour market and industrial policies**
 - **facilitate** investments in **new technologies**
 - **spread benefits and costs** across a larger pool of firms and workers.

Thank you for your patience!

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Appendix

Identification of natural disasters

- To be recorded in the EM-DAT database, an event must fulfil at least one of the following conditions:
 1. 10+ people killed;
 2. 100+ people affected/injured/homeless;
 3. a state of emergency has been declared;
 4. call for international assistance.
- We keep only disasters that meet the first two conditions and include a further condition:
 1. the event affected $\geq 0.5\%$ of the country's population
or
 2. caused a damage $\geq 0.05\%$ of GDP

▶ Back

Disaster types

- climatological
 - drought
 - wildfires
- meteorological
 - storms
 - extreme temperatures
- hydrological
 - floods
 - avalanches
 - landslides

▶ Back

- A number of papers have exploited data on natural disasters and extreme weather conditions taken from the Emergency Events Database (EM-DAT).
- We compare our baseline proxy with the ones used in four recent papers:

	This paper	Gu and Hale (2023)	Feng, et al.(2023)	Ferriani et al. (2024)	Hale (2022)
Macrogroups					
climatological	✓	✓	✓	✓	✓
meteorological	✓	✓	✓	✓	✓
hydrological	✓	✓	✓	✓	✓
geophysical				✓	
Selection rules					
10+ deaths	-	-	-	-	✓
10+ deaths or 100+ people affected or state of emergency/call for IA	✓	✓	✓	✓	
>0.5% population affected or damage >0.05% of GDP.	✓	✓			
Unit of analysis					
	Level-2 admin. units (subnational)	Country	Country	Country	Country
Period					
	2009-2019	2007-2019	1970-2019	2009-2019	1964-2019

- Our measure of automation is based on detailed firm-level customs data on imports of machines from abroad
- Following [Aghion et al. \(2020\)](#), we identify a group of automation technologies belonging to two main categories:
 - HS84 "Nuclear reactors, boilers, machinery and mechanical appliances; parts thereof"
 - HS85 "Electrical machinery and equipment and parts thereof; sound recorders and reproducers, television image and sound recorders and reproducers, parts and accessories of such articles".
- We exclude several detailed product categories related to ICT and transportation.
- We retain 420 categories out of 1338 belonging to the two macro-groups.

Matched employer-employee data - Summary statistics

	mean	st dev	5th perc	median	95th perc	N
Panel A: Workers in international business groups	(1)	(2)	(3)	(4)	(5)	(6)
Male	0.62	0.475	0	1	1	1,630,167
Age	39.9	11.41	22	40	58	1,630,167
Working hours	1480	651.6	302	1819	2200	1,630,167
Hourly Wage	21.48	13.6	9.4	17.7	43.2	1,630,167
Incumbent	0.78	0.4119	0	1	1	1,630,167
Distance	37.6	98.5	1.01	10.7	179.8	1,630,167
Panel B: Workers in other firms	(1)	(2)	(3)	(4)	(5)	(6)
Male	0.65	0.488	0	1	1	14,700,000
Age	37.82	11.95	20	37	58	14,700,000
Working hours	1313	651.6	37	1560	2119	14,700,000
Hourly Wage	16.91	13.6	8.9	13.43	35.46	14,700,000
Incumbent	0.72	0.449	0	1	1	14,700,000
Distance	30.57	90.2	0.46	8.5	118	14,700,000

▶ Back

Subsidiary-level analysis - No previous exposure

Dep. Var.: Divestment	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Natural disaster	0.0425*** (0.00835)	0.0580*** (0.0120)	0.0491*** (0.00870)	0.0468*** (0.0087)		0.0449*** (0.00871)	0.0655* (0.0365)
Natural disaster#Parent historic risk exposure		-0.0244* (0.0136)					
Natural disaster#logDistance			0.0104*** (0.00330)				
Natural disaster#Routine task intensity				0.0024 (0.0026)			
Natural disaster#2nd Layer					-0.00429 (0.00783)		
Natural disaster#3rd Layer					0.0698*** (0.00957)		
Natural disaster#4th Layer					0.102*** (0.0131)		
Observations	899,383	865,180	865,180	865,094	865,180	672,959	164,859
R-squared	0.720	0.718	0.718	0.718	0.719	0.725	0.723
Subsidiary FE	✓	✓	✓	✓	✓	✓	✓
Destination Country#Industry#Year FE	✓	✓	✓	✓	✓	✓	✓
Parent firm#year FE	✓	✓	✓	✓	✓	✓	✓
IncomeGroup	All	All	All	All	All	HI	MLI

- Results are confirmed when accounting for heterogeneous shock intensity and focusing only on low-risk regions (regions that did not record any natural disaster between 1990 and 2010). [▶ Back](#)

Subsidiary-level analysis - Breakdown by Shock Type

	(1)	(2)	(3)	(4)
Dep. Var.: Divestment				
Climatological Disaster	0.0596*** (0.00799)			0.0571*** (0.00870)
Hydrological Disaster		0.0247*** (0.00781)		0.0252*** (0.00814)
Meteorological Disaster			0.0229** (0.00997)	0.0239** (0.0103)
Observations	4,126,908	4,126,908	4,126,908	4,126,908
R-squared	0.681	0.681	0.681	0.681
Subsidiary FE	✓	✓	✓	✓
Parent firm#year FE	✓	✓	✓	✓
Destination Country#Industry#Year FE	✓	✓	✓	✓

Subsidiary-level analysis - Natural disaster intensity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.: Divestment							
Natural Disaster	0.00603* (0.00331)	0.00965*** (0.00348)	0.00511*** (0.00181)	0.00566*** (0.00172)	0.00520*** (0.00154)	0.00526*** (0.00155)	0.0100*** (0.00327)
Observations	5,889,828	5,146,797	4,131,607	4,131,607	4,053,284	4,000,045	4,126,908
R-squared	0.335	0.375	0.672	0.672	0.672	0.670	0.681
Subsidiary FE	✓	✓	✓	✓	✓	✓	✓
Parent country#year FE	✓	✓	-	-	-	-	-
Year#IncomeGroup#Region#Industry FE	-	✓	✓	✓	✓	✓	-
Parent firm#year FE	-	-	✓	✓	✓	✓	✓
Destination Country#Industry#Year FE	-	-	-	-	-	-	✓

▶ Back

BG-level analysis - No previous exposure

	(1)	(2)	(3)	(4)	(5)
Dep var.: Δ Affiliates					
Natural Disasters	-0.172*** (0.0280)	-0.166*** (0.0264)	-0.198*** (0.0300)	-0.169*** (0.0439)	-0.185** (0.072)
Observations	2,190,298	2,190,170	269,266	552,143	65,027
R-squared	0.158	0.162	0.175	0.197	0.140
BG FE	✓	✓	✓	✓	✓
Year FE	✓	-	-	-	-
Parent country \times Year FE	-	✓	✓	✓	✓
Parent country	All	All	All	All	France
BG size	All	All	≥ 5	All	All
Home country risk level	All	All	All	Below average	All

- Results are confirmed when accounting for heterogeneous shock intensity and focusing only on low-risk regions (regions that did not record any natural disaster between 1990 and 2010).

Business group-level analysis - Heterogeneity

VARIABLES	(1)	(2)	(3)	(4)
	Δ Affiliates	Δ Affiliates (1st layer)	Δ Affiliates (2nd layer)	Δ Affiliates (3rd+ layer)
Panel A: 1 layer BG				
Natural disasters	-0.0640*** (0.00479)			
Observations	1,427,607			
R-squared	0.136			
Panel B: 2 layers BG				
Natural disasters	-0.0746*** (0.00540)	-0.113*** (0.0108)	-0.0984*** (0.00831)	
Observations	494,791	494,791	494,791	
R-squared	0.140	0.145	0.115	
Panel C: 3+ layers BG				
Natural disasters	-0.155*** (0.0206)	-0.0700*** (0.0189)	-0.152*** (0.0276)	-0.116*** (0.0165)
Observations	267,391	267,391	267,391	267,391
R-squared	0.174	0.114	0.150	0.187
BG FE	✓	✓	✓	✓
Parent country \times Year FE	✓	✓	✓	✓

BG-level analysis - Narrow Offshoring

- We exploit firm-level customs data provide direct evidence on the effect of natural disasters on reshoring dynamics.
- Feenstra and Hanson, 2003 define 'narrow offshoring' as the procurement of inputs from the same industry as the producing firms.
- Following Hummels et al. (2014), we define narrow offshoring as the total intermediate imports within the same 4-digit CPA2.1 category as the goods sold by the firm.
- We estimate the following specification:

$$\ln I_{jc_i kt} = X'_{j,t-1} \beta_1 + \beta_2 ND_{c_i,t-1} + \gamma_{jc_j} + \lambda_{kt} + \varepsilon_{jc_i kt} \quad (5)$$

- $I_{jc_i kt}$: intermediates or same-industry intermediates traded between firm j and country c_i
- $ND_{c_i,t-1}$: dummy switching the year after the partner country is hit by a natural disaster
- $X'_{j,t-1}$: vector of firm-level characteristics
- $\gamma_{jc_j}, \lambda_{kt}$: firm \times partner country and industry \times year fixed effects

BG-level analysis - Narrow Offshoring

Dep var.	In intermediates			
	(1)	(2)	(3)	(4)
Natural disaster	-0.0239*** (0.006)	-0.0236*** (0.007)	-0.0001 (0.0004)	-0.0377*** (0.0078)
Observations	1,047,077	975,295	276,768	584,330
R-squared	0.62	0.78	0.83	0.78
In Same-industry intermediates (narrow offshoring)				
	(5)	(6)	(7)	(8)
Natural disaster	-0.116* (0.06)	-0.0948 (0.066)	-0.05 (0.081)	-0.185*** (0.090)
Observations	561,021	549,530	276,768	343,983
R-squared	0.78	0.85	0.83	0.85
Countries	All	All	HI	MLI
Firm×Partner country FE	✓	✓	✓	✓
Year FE	✓	-	-	-
Industry×Year FE	-	✓	✓	✓

Investments in industrial robots

- Focus on 'robot adopters' (Aghion et al., 2020; Acemoglu, Koster, et al., 2023)

Dep var.	Robot adopter			
	All manufacturing		Automation-intensive industries	Other industries
	(1)	(2)	(3)	(4)
Direct exposure	0.161*** (0.0284)	0.0221** (0.0112)	0.0394* (0.0231)	0.0167 (0.0120)
Observations	47,793	47,489	18,583	28,844
R-squared	0.004	0.916	0.912	0.918
Firm FE	-	✓	✓	✓
Year×Industry FE	-	✓	✓	✓

- The shock increases by 2% the probability to become a robot adopter
- Effect driven by automation-intensive sectors

Controlling for Non-Random Exposure (Borusyak & Hull, 2023)

- Shock exposure may not be random.
 - For example, firms experiencing rapid growth may have disproportionately invested in risk-prone regions.
- To address this, we apply the methodology proposed by [Borusyak and Hull \(2023\)](#).
- The approach involves incorporating a proxy for 'non-random exposure' into the analysis.
- Procedure:
 - Group natural hazards into [macro-categories](#).
 - For each shock type, [permute disaster dates across regions](#) while maintaining the total number of disasters per region.
 - Generate [1,000 counterfactual distributions](#) of natural disasters over time.
 - Compute the [average shock exposure](#) for each region-year unit and derive the BG-level exposure to the synthetic shock.
- Including this control isolates the 'unexpected exposure' to natural hazards.

Controlling for non-random exposure (Borusyak & Hull, 2023)

	(1)	(2)	(3)	(4)	(5)	(6)
	Employment	Employment	Intermediates	Intermediates	Machinery	Machinery
All						
Disaster exposure	0.00224 (0.00256)	0.00386 (0.00257)	-0.0233* (0.0135)	-0.0294** (0.0141)	0.0472** (0.0234)	0.0548** (0.0237)
Observations	43,983	43,967	54,588	54,581	54,044	55,036
R-squared	0.958	0.959	0.872	0.877	0.777	0.779
Automation-intensive sectors						
Disaster exposure	0.0036 (0.00337)	0.00503** (0.00347)	-0.0011 (0.0223)	-0.00435 (0.0215)	0.0642** (0.0313)	0.0721** (0.032)
Observations	25,449	25,483	28,145	28,138	28,101	28,093
R-squared	0.965	0.965	0.863	0.868	0.729	0.731
Other sectors						
Disaster exposure	0.00067 (0.00392)	0.00233 (0.00378)	-0.0524*** (0.0134)	-0.0619*** (0.0139)	0.0214 (0.0354)	0.0262 (0.0351)
Observations	18,443	18,443	26,339	26,339	26,889	26,889
R-squared	0.949	0.951	0.882	0.887	0.774	0.775
Counterfactual shock control	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Industry×Year FE	-	✓	-	✓	-	✓

Controlling for non-random exposure (Borusyak & Hull, 2023)

Dep var.	Hourly Wage					
	All manufacturing		Robot-intensive industries		Other industries	
	(1)	(2)	(3)	(4)	(5)	(6)
Natural disasters	0.0598** (0.0025)	0.0673** (0.0262)	0.0706** (0.0291)	0.0798** (0.0307)	0.0131 (0.0141)	0.0171 (0.0145)
Routine cognitive		-0.0203*** (0.00197)		-0.0188*** (0.00243)		-0.0263*** (0.00374)
Natural disasters x Routine cognitive		-0.0294*** (0.0077)		-0.0343*** (0.0097)		-0.0205* (0.0112)
Observations	1,597,361	1,597,361	1,144,855	1,144,855	642,094	642,094
R-squared	0.909	0.909	0.903	0.903	0.922	0.922
Counterfactual shock control	✓	✓	✓	✓	✓	✓
Worker FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Industry×Year FE	✓	✓	✓	✓	✓	✓