Natural Disasters, Reshoring Dynamics and Automation*

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This study examines the relationship between reshoring and automation in a context shaped by growing uncertainty and rapid technological advancements. We analyse how idiosyncratic shocks to foreign subsidiaries of multinational business groups prompt a reduction in international activities, driving shifts in the parent firm's skill composition and domestic investment in automation. Our analysis leverages new geolocated data covering over 8 million foreign affiliates, firm-level customs data, and a unique matched employer-employee dataset covering the universe of French firms and workers. Our findings reveal that natural disasters affecting foreign affiliates significantly increase parent firms' propensity to adopt automation technologies and positively affect domestic wages. This effect is more pronounced for non-routine task intensive occupations and is largely confined to robot-intensive sectors. Conversely, the impact on other industries is negligible. These results suggest that firms operating in automation-intensive industries react to adverse shocks affecting their foreign affiliates by replacing low-skilled foreign labour with domestic automation.

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1 Introduction

In recent years, the global economy has been characterised by large and frequent economic uncertainty shocks,[1] a rapid process of geo-economic fragmentation,[2] and the advent of new technologies capable of performing an expanding range of tasks (Antràs, 2020). In this evolving economic environment, governments have put in place policies to reduce the exposure of their economies to external shocks while favouring domestic employment. Reshoring foreign activities while bringing jobs back home is increasingly seen as a win-win strategy, capable of attracting bipartisan support on the global political stage. However, despite widespread anecdotal evidence, empirical studies have found only a limited impact of reshoring on domestic labour markets (Dachs & Zanker, 2015; De Backer et al., 2016). One possible explanation for these modest effects is the increasing role of automation technologies in replacing tasks previously performed by low-skilled foreign workers.

The relationship between exogenous shocks, automation, and reshoring dynamics is theoretically ambiguous. On one hand, increased uncertainty can promote reshoring if firms perceive the domestic economy as more stable and less vulnerable to shocks (Faber et al., 2023; Grossman et al., 2023). Conversely, firms might find it more efficient to diversify the production process across many regions, and investing substantial resources in a new technology within a single country may appear less appealing. Additionally, the partial loss of sunk investments abroad can lower the opportunity cost for firms to shift production back home and invest in automation (Krenz et al., 2021). This scenario, however, only applies to sectors where automation is economically viable. Even in the presence of automation-enhanced reshoring dynamics, the negative displacement effect could be partially offset by a positive productivity effect, which could lead firms to increase the imports of (non-automated) inputs (Artuc et al., 2023).

This paper contributes to the ongoing debate on the relationship between reshoring

[1] Over the last two decades, the global economy was hit by the European debt crisis, Brexit, the US-China trade war, the Covid-19 crisis, the Russian invasion of Ukraine, and frequent and unpredictable natural disasters.

[2] This term has recently been used by (IMF, 2023) to define a policy-driven reversal of economic integration, which takes the forms of economic decoupling, development of regional economic blocks, and supply chain diversification.

and automation by showing that idiosyncratic shocks to foreign affiliates can lead to the partial relocation of tasks from foreign workers to domestic machines. We obtain this result by examining the impact of natural disasters on foreign activities of large multinational business groups. The correct identification of the impact of reshoring on domestic automation and employment composition requires separating these processes from broader internationalisation strategies of business groups. It is possible that decisions about domestic automation are actually driving reshoring strategies, rather than being a response to global instability and shocks. Addressing this critical identification challenge requires linking reshoring decisions to shocks that are exogenous in nature and uncertain in timing. Local natural disasters, external to the automation trajectory of the parent company, can significantly influence the technology adoption decisions of the parent company due to the loss of prior investments and unrecovered fixed costs in foreign locations. Additionally, such shocks can lead to a re-evaluation of the risks involved with foreign operations in unaffected locations, resulting in a comprehensive restructuring of the entire business group.

Our empirical strategy involves two main steps. First, we map the occurrence of natural disasters (climatological, geophysical, and meteorological hazards) at a highly granular level globally and analyse how these idiosyncratic shocks impact over 8 million affiliates of international business groups. To our knowledge, this is the first paper to identify affected firms based on a subnational measure of exposure to natural disasters. This means that, contrary to previous analyses, we do not assume nationwide effects in large countries like China or India. Moreover, by constructing a multilayer ownership network, we can examine the impact of a natural disaster based on a subsidiary's position within this network and its relationship with the parent firm. Although natural disasters can typically be viewed as exogenous shocks, business groups that are less risk-averse might be more inclined to invest in regions prone to such risks. To address this concern, we account for firm- and business group-specific characteristics and replicate the entire analysis by focusing exclusively on areas that did not experience natural hazards over the previous two decades.

Next, we focus on parent firms and estimate the impact of foreign idiosyncratic shocks

- natural disasters - on domestic investment in automation technologies and on the demand for different types of domestic workers. For this purpose, we narrow down the focus to France, a country that accounts for over 4% of the global stock of foreign indirect investments.[3] Using a matched employer-employee dataset that covers the entire manufacturing sector workforce, we investigate firm- and worker-level effects of foreign affiliate exposure to natural disasters. Additionally, our analysis offers a new perspective on the analysis of wage effects of automation technologies. While previous research has primarily examined the labour market effects of automation through changes in technological efficiency (Acemoglu et al., 2023; Aghion et al., 2020; Bessen et al., 2020; Bonfiglioli et al., 2020), we focus instead on exogenous shifts in the opportunity cost of investing in automation technologies.

Our results demonstrate that foreign idiosyncratic shocks in the form of natural disasters significantly heighten the probability of divestment from the affected subsidiaries. These shocks then propagate through the business group network and affect the skill composition and technology of the parent firm. Firms whose foreign affiliates are hit by an unexpected shock are more likely to invest in automation at home. Interestingly, this effect is significant only for firms in automation-intensive industries, suggesting that firms can replace foreign workers with domestic automation technologies only in sectors where these technologies are already mature. On average, the exposure to foreign shocks has a positive effect on domestic wages. However, this effect is concentrated in automation-intensive industries, where the shock fosters investment in automation and workers can potentially benefit from pro-competitive effects. From an occupational perspective, we find that non-routine workers benefit more than other worker types.

Our findings are robust to several potential threats to identification. Specifically, we provide evidence that exposure to natural disasters is uncorrelated with pre-existing trends in employment and investment, mitigating concerns about endogeneity. Additionally, following the methodology proposed by Borusyak and Hull (2023), we confirm that the observed shocks can be considered as-good-as-random, reinforcing the credibility of our identification strategy.

[3] In 2023, France recorded an outflow FDI stock of €1,635 billion.

The structure of the paper is as follows. Section 2 reviews the relevant literature. Section 3 introduces the data. Section 4 presents preliminary macro-level evidence. The main empirical models and results are discussed in Section 5. Specifically, Sections 5.1 and 5.2 present the subsidiary- and business group-level estimates, while Sections 5.3.1 and 5.3.2 focus on the parent-level analysis, examining firm- and worker-level outcomes, respectively. Finally, Section 6 concludes the paper and offers policy-relevant insights.

2 Literature

This paper sits at the intersection of two strands of literature. On the one hand, it adds to the growing body of research examining the international transmission of idiosyncratic shocks through the network structure of business groups. On the other hand, it advances the literature on the effects of automation technology adoption on firms and workers.

Nowadays, the global economy is dominated by cross-country and cross-industry supply chains, where domestic and transnational firms contribute to the production of final products. Several studies have shown that a small subset of multinational firms, accounting for a large share of aggregate economic activity, are responsible for the bulk of international trade (e.g., Mayer and Ottaviano, 2008; Freund and Pierola, 2015).[4]

Building on these insights, a recent literature has analysed the role of multinational firms in the transmission of shocks across countries. Early contributions, mostly focusing on cross-sectoral propagation of shocks, found mixed empirical evidence about the importance of such linkages (Barrot & Sauvagnat, 2016; Long Jr & Plosser, 1983). Later studies have provided more robust evidence about their pivotal role by shifting the attention from sector- to firm-specific shocks (Di Giovanni et al., 2014; Carvalho and Grassi, 2019; Gaubert and Itskhoki, 2020 among others).[5] Recently, Bena et al. (2022) has shown that the propagation of local shock can go beyond the direct parent-subsidiary relationship and involve all the affiliates belonging to the same business group.

A specific strand of this literature has focused on the propagation of natural disasters through trade and ownership linkages. There is a consensus in the climate science literature that the occurrence and intensity of natural disasters are increasing everywhere due to climate change (Hsiang & Kopp, 2018; Pachauri et al., 2014). While the distribution of these disasters remains largely uneven across space, disruptions within any segment of

[4]On average, two-way traders account for 15% of all trading companies, and yet they capture almost 80% of total trade (WTO, 2020) Moreover, while trade in final goods is by nature volatile, trade in intermediates is relational, generally conducted by companies that engage in repeated interactions, making them "sticky" (Antràs, 2020).

[5]At the same time, this empirical evidence and the availability of microdata on firm ownership and international transactions have inspired a recent literature on the micro-origins of international business-cycle co-movement (Kleinert et al., 2015; Di Giovanni et al., 2018; Cravino and Levchenko, 2017; C. Boehm and Kroner, 2020)

the global supply chain can have profound economic consequences for international trading partners. Emerging research has examined how the impact of climate-related events spreads through trade and production networks, impacting the performance of internationalised firms (C. E. Boehm et al., 2019; Carvalho & Grassi, 2019; Dingel et al., 2019; Feng & Li, 2021; Feyrer, 2021; Forslid & Sanctuary, 2023; Gu & Hale, 2023).[6]

This study builds on this literature by analysing a specific mechanism by which natural disasters - identified at a sub-national level - propagate through ownership networks. In line with the existing literature on foreign investment, we posit that a firm establishing a production plant abroad incurs a sunk investment cost. This cost encompasses the initial expenditures related to searching for a partner or suitable investment site, negotiating a contract, designing an appropriate input, and investing in physical assets (Grossman et al., 2023). In an environment characterised by information asymmetries and imperfect insurance markets, these sunk costs enhance the stickiness of past investment decisions (Di Stefano et al., 2022; Dixit & Pindyck, 1994; Fillat & Garetto, 2015). It follows that the initial decision to offshore production activities abroad is not equivalent to the subsequent decision to reshore the same activities (Antràs, 2020; Grossman et al., 2023). Within this framework, natural disasters can lead to a partial or complete loss of the sunk investment, in the form of destruction of fixed capital, disruption of the local supply network and political instability (and following loss of 'relational capital'). Moreover, an unexpected local shock can change the parent firm's assessment of its overall risk exposure and lead to an overall restructuring of the business group.[7] This dynamic is confirmed by a growing body of literature in financial economics suggesting that natural disasters are 'salient events' that can significantly influence both corporate managers and asset prices (Alok et

[6]Two specific studies directly focus on the effect of natural disasters on global value chains and foreign direct investments. Feng and Li (2021) find that the effects of natural disasters can propagate to the affected country's primary international partners. The authors conduct a country-level analysis associating each climate disaster with the directly impacted nation and its key trade partners, both upstream and downstream. Their findings underscore that a natural disaster can significantly disrupt the macroeconomic and financial stability of the trade partners, especially if it impacts a critical transport node like a port. Gu and Hale (2023) find that firms with high climate risk exposure are more likely to reduce FDI in response to the target country's climate risks following the 2015 Paris Climate Accord.

[7]As highlighted by Grossman et al. (2023), if the parent firm perceives the domestic economy as less vulnerable to future shocks, it might find it convenient to reshore back economic activities to the home country. Conversely, if the home country is perceived as equally exposed, firms might find it more efficient to diversify the production process across many regions.

al., 2020; Bernile et al., 2017; Dessaint & Matray, 2017; Gustafson et al., 2023; Huang et al., 2022; Kruttli et al., 2021). As a result, these shocks can decrease the opportunity cost of reshoring and accelerate the substitution of foreign labour with domestic automation. In this study, we test this hypothesis by investigating the impacts of shock-induced reshoring decisions on skill composition and technological adoption in parent firms.

This paper also contributes to the growing literature on the effects of automation on labour markets. Traditionally, the labour economics literature has emphasised the risk of job replacement (displacement effect) associated with a rapid diffusion of automation (Brynjolfsson & McAfee, 2014; Keynes et al., 1930; Leontief, 1952). Over the last decade, the literature has identified two mechanisms that could partially offset these negative effects. On the one hand, the productivity boost guaranteed by automation could help firms expand their market share and thus their workforce (productivity effect).[8] On the other hand, automation can generate new tasks (reinstatement effect) which are, at least at in the short run, non-automatable, thereby increasing demand for labour (Acemoglu & Restrepo, 2020; Aghion et al., 2020; Yan & Grossman, 2023).

A recent empirical literature has tried to test these alternative predictions using firm-level data.[9] Among these studies, only three contributions try to identify the effect of automation on firm-level outcomes within a causal framework (Acemoglu et al., 2023; Aghion et al., 2020; Bessen et al., 2020; Bonfiglioli et al., 2020).[10] The general consensus is that automation has a positive effect on indirectly affected workers[11] operating in robot-adopting firms, driven by skill-biased productivity effects and reinstatement effects. On

[8]This second mechanism could lead to a null or even negative effect on domestic employment at the aggregate level (Acemoglu & Restrepo, 2020; Acemoglu et al., 2020).

[9]Some of these studies proxy automation with robot imports (Humlum, 2022 for Denmark, Dixon et al., 2021 for Canada, Acemoglu et al., 2020 for France, Acemoglu et al., 2023 for the Netherlands), while others use dummies from survey data (among others, Koch et al., 2021 for Spain, Cheng et al., 2019 for China, Dinlersoz and Wolf, 2023 for the U.S.).

[10]The first one is Bessen et al., 2020, who use matched employer-employee data for the Netherlands. Aghion et al. (2020) focus on France and proxy automation with investment in industrial equipment and robot imports. The paper exploits a shift-share IV strategy, based on exogenous changes in the world export supply of automation technologies. Finally, Bonfiglioli et al. (2020) studies firm exposure to automation, expressed as the interaction between industry-level suitability to automation and firm-level replaceability of employment.

[11]Directly affected workers are identified by the routine task content (measured using the O*NET occupational classification) or another measure of replicability (such as the one proposed by Graetz and Michaels (2018)), while other workers are classified as 'indirectly affected'.

the other hand, directly affected workers employed by competing firms are negatively affected. The effect on other workers is ambiguous and depends on product demand elasticity and the degree of worker substitutability.

Recently, the debate on the interplay between these forces has inspired a new literature on the relationship between reshoring and automation. In the 1970s, only a few firms in specific sectors utilised industrial robots. At that time, the primary strategy for reducing labour costs in the production of labour-intensive goods involved offshoring manufacturing to low-income countries. However, since the early 1990s, the use of industrial robots has surged, and today they are a key component in the production processes of most manufacturing industries (IFR, 2022). In this scenario, the shift of manufacturing back from low-wage to high-wage countries may predominantly lead to increased automation rather than substantial job creation. Krenz et al. (2021) develop a comprehensive theoretical framework in which increasing productivity of automation technologies leads to a relocation of previously offshored production back to the home economy, increasing the demand for skilled workers and thus the domestic skill premium. These theoretical predictions are supported by some recent empirical studies.[12] In contrast, Artuc et al. (2023) argue that automation in high-income countries can increase demand for inputs from low-income countries.[13] In their model, the productivity gains experienced by the robot adopters in the North increase the demand for certain inputs from the South, ultimately counterbalancing the displacement effects typically associated with tasks more susceptible to automation.[14]

These competing narratives stem from different assumptions: Krenz et al. (2021) assume production relies on a single intermediate input that firms can source domestically or internationally. In contrast, Artuc et al. (2023) assume a continuum of foreign tasks that firms in high-income countries can outsource, implying some tasks may continue abroad and experience demand increases. Furthermore, while Krenz et al. (2021) con-

[12] Stemmler (2019) show that exposure to foreign automation affects employment in foreign earned Brazilian manufacturing firms. Faber (2020) demonstrate that exposure to U.S. automation affects exports and labour market conditions in Mexico.

[13] The authors develop a simple task-based Ricardian model featuring a two-stage production process and trade in intermediate and final goods to examine the implications of automation for trade flows between low- and high-income countries, wages and welfare.

[14] Hallward-Driemeier and Nayyar (2019) (for the US) and Stapleton and Webb (2020) (for Spain) provide evidence for this hypothesis, by showing positive impacts of automation intensity in high-income countries on imports sourced from, or FDI growth to, low-income countries, respectively.

sider shocks in both automation productivity and trade costs, Artuc et al. (2023) focus solely on automation efficiency. An indirect contribution to this debate is provided by Faber et al. (2023), who find that increased uncertainty in developing economies encourages reshoring in automation-intensive sectors within high-income countries. Overall, the literature presents an ambiguous relationship between reshoring and automation, which depends on the interplay between displacement and productivity effects as well as on the driver of the shock.

This study contributes to the debate by identifying a distinct channel whereby reshoring influences domestic automation. While previous empirical literature exploits exogenous changes in robots' efficiency, we leverage natural disasters as exogenous shocks which reduce the opportunity costs of replacing foreign plants with domestic automation technologies.

3 Data and descriptives

This study exploits a unique combination of large microdatasets retrieved from different sources. In Table 1 we report a general overview of the main datasets used. The first part of the paper, which examines the effect of natural disasters on foreign affiliates, uses sub-national data on natural disasters, an international business group dataset mapping ownership linkages across over 8,000,000 foreign affiliates located around the world, as well as global country-product and France-specific firm-country-product bilateral trade data. These data are further complemented by country-industry level data on the adoption of industrial robots. The second part of the paper extends the analysis to the automation adoption effects of natural disasters, linking the above data with a panel matched employer-employee dataset that covers the entire population of French private-sector workers, along with detailed data on firm investments in automation technologies. Finally, we further enrich our analysis with measures of task content by occupation. In the following sections, we briefly present the various datasets used.

Table 1: Final dataset summary

Dataset	Spatial coverage	Sectors	Unit of observation	Period	Avg. N. of observations
EM-DAT	World	-	Level 1 administrative units	1990-2019	3,606
IFR	World	All	Country-industry	1990-2019	4,500
Orbis	World[15]	All	Firm	2009-2019	834,355
FARE	France	Manufacturing	Firm	2009-2019	380,354
Customs data	France	Manufacturing	Firm-country-product-level transactions	2002-2019	945,448
DADS	France	Manufacturing	Worker	2002-2019	2,487,655

3.1 Natural disasters

Data on natural disasters are retrieved from Emergency Disasters Database (EM-DAT),[16] collected by the University of Louvain, cataloguing global disaster occurrences from 1900 to present. The dataset currently includes around 24,500 natural disasters.[17] To be recorded

[16] Several papers have compared the Emergency Disasters Database with other datasets about natural disasters and climate change, such as NatCat, Sigma, and DesInventar (See for instance Panwar and Sen, 2020 and Franzke, 2021). These studies confirm the high reliability of this dataset, especially from 1990 onwards.

[17] The EM-DAT dataset covers 9 macro-groups of disasters. We drop the man-made (biological, industrial and transport disasters) and the extra-terrestrial ones. Our final dataset only includes climatological

in the database, an event must fulfil at least one of the following conditions: (i) ten or more people reported as killed; (ii) one hundred people reported as affected, injured, or homeless; (iii) a state of emergency has been declared; (iv) the country has issued a call for international assistance.

In this study, we further restrict the dataset based on the criteria proposed by the International Monetary Fund (Monetary & Dept., 2020), by selecting only events that affected more than 0.5% of the country's population or caused damage greater than 0.05% of GDP, as reported in the year prior to the shock. Regional data on population and GDP were retrieved, respectively, from the GPW dataset, developed by CIESIN at Columbia University,[18] and from the DOSE dataset, produced by the Mercator Research Institute on Global Commons and Climate Change (MCC) and the Potsdam Institute for Climate Impact Research (PIK).[19] This approach is in line with a recent literature at the intersection between environmental economics and international trade.[20] The original EM-DAT dataset only provides unstructured information on the exact extent of the disaster within each country. In order to get a more detailed spatial breakdown, we first merge EM-DAT with the Geocoded Disasters Dataset (GDIS) (Rosvold & Buhaug, 2020), which provides the exact coordinates of the geographical areas affected for a large sample of disasters. Subsequently, we implement a matching algorithm to assign the remaining regions to a GADM level-2 administrative unit.[21]

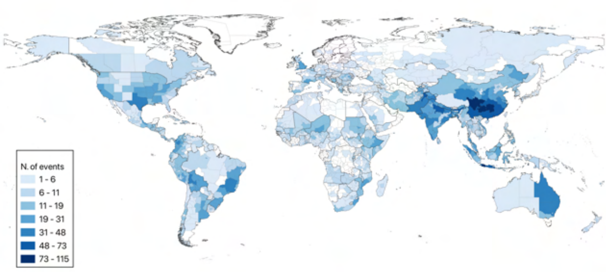
(drought and wildfires), geophysical (earthquakes and volcanic activities), meteorological (storms and extreme temperatures) and hydrological (floods, avalanches, landslides, and mudslides) disasters. During the period 2010-2023, these disasters accounted for 64% of the total number of disasters recorded in the dataset, 81% of the deaths, and over 98% of the total monetary damage

[18]The dataset models the distribution of population on a continuous global raster surface.

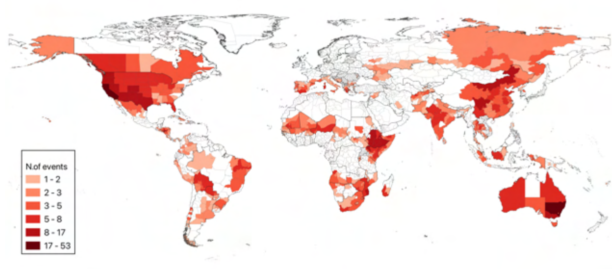
[19]The dataset covers 77 countries and is mostly based on information retrieved from various statistical agencies of central or federal governments as well as from yearbooks.

[20]see for instance Gu and Hale, 2023 and Feng and Li, 2021. In Appendix B.1.1, we compare our proxy with other proxies used in the literature.

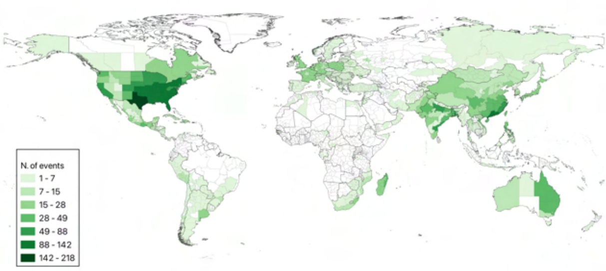
[21]The Database of Global Administrative Areas (GADM) is a high-resolution database of country administrative areas. The dataset includes six levels of administrative divisions: National (level 0), State or Province (level 1), County or District (level 2), Commune or Municipality (level 3), and two smaller subdivisions at Levels 4 and 5.



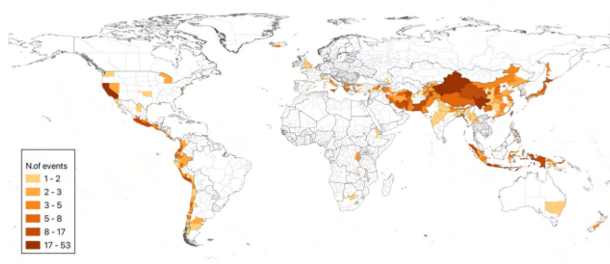
(a) Hydrogeological



(b) Climatological



(c) Meteorological



(d) Geophysical

Figure 1: N. of disasters, 1970-2019

The final dataset provides information on 3,600 sub-national Administrative Units. For each region, we access the monthly counts of fatalities, affected individuals, and financial damage in U.S. dollars, as well as regional-level information to be used to normalise the intensity measures. Figure A1 shows the occurrence of the four main types of disasters over time, whereas Figure 1 depicts the most affected regions over the period 1970-2019.

3.2 Ownership network data

Data on global ownership and financial accounts of foreign subsidiaries are retrieved from Orbis, a firm-level database compiled by Bureau Van Dijk which covers more than 170 million companies globally and broadly acknowledged as a highly comprehensive and reliable source of global corporate performance data. For this project, we use the Orbis

Historical product, which tracks companies over time. Regarding data cleaning, we implement several adjustments to the original dataset. Among other things, we drop entries for companies listed multiple times in the dataset (as per the method in Bajgar et al., 2020), by maintaining records of their unconsolidated financial accounts. This approach addresses instances where a company may be represented multiple times in a single year with both consolidated and unconsolidated financial statements. Furthermore, we omit businesses in primary sectors such as agriculture and mining, as well as those in the public sector including education and health. Lastly, to enhance the reliability of our findings, we exclude firms with inadequate financial records, as these are often estimated and of lower quality. We then map business networks using an iterative process similar to the one used by Rungi et al. (2017). Starting from ultimate owner firms, we progressively identify ownership linkages by direct control, transitivity, consolidation of voting rights, and dominant stake. Through this procedure, we construct a comprehensive multilayer ownership network for over 600,000 parent firms,[22] covering over 8 million foreign affiliates.

Unlike previous studies, we replicate the procedure for the whole period 2009-2021, obtaining a subsidiary-level panel dataset. A comprehensive outline of our data cleaning and ownership mapping methodologies is provided in Section B.1.2.1 in the Appendix.

3.3 Parent-firm level data

In the second part of the paper, we focus our analysis on the effect of idiosyncratic shocks on parent firms in France, which we can link to their business group through their ORBIS identifier and for which we can access balance sheet data, firm-level data on international transactions, as well as a panel matched employer-employee dataset. Although our data cover all workers and firms in the economy, for the purpose of this study we specifically focus on manufacturing firms[23] that belong to a France-based multinational business group. Table A2 in Appendix A.3 reports summary statistics by macro-industry for the sample and the relative share of the business group over the whole economy. While only 1% of French manufacturing firms participate in a business group, they represent 18% of the

[22] We only consider business group which over the period considered recorded at least one foreign affiliate in a given year

[23] We adopt a broad definition of manufacturing, which includes mining and construction

overall employment and 23% of value added.

3.3.1 Balance sheet data

The firm dataset FARE (Fichier Approaché des Résultats d'Esane), from INSEE/DGFiP, is a collection of tax fillings by firms for corporate income tax. It provides the complete balance sheets of firms, including information on total sales, number of employees, location, industry, and date of opening and closure of all firms in the data. Moreover, we have information on investments in 'Machinery, equipment and tools' (*AR - Installations techniques, matériel et outillage industriel*), which we use to build one of our proxies for investments in machinery. Since firms need to report every year to the tax authorities, it covers the whole population of French firms from 2008 to 2021 (28 million observations) with no limiting threshold in terms of firm size or sales. By merging the dataset with information provided by the Repertoire Sirene, we can assign an address and precise spatial coordinates to 27 million establishments (the entire population of establishments that have ever operated in France over the last 20 years).

3.3.2 Trade data

Firm-level trade data are retrieved from an exhaustive administrative dataset produced by French Customs. For each firm, the yearly value of imports and exports (by country of origin/destination and 8-digit CN product) are reported for the period 1995-2023. We retain only manufacturing firms and exclude raw materials (HS01-15, 23, 25-27, 31, and 41), and services (HS97-99). When the partner is not an EU member state, only transactions above €1,000 are recorded. For EU countries, there is no transaction-specific threshold, but transactions are reported only when the overall annual import/export flow is above €1.2 million. For consistency, we drop all extra-EU transactions below €1,000 (expressed in 2009 real values) and disregard intra-EU trade flows for all firms that fall below the EU threshold at least once over the period under consideration. The final dataset contains over 16 million annual firm-product-country-level observations, concerning 5,000 CN8 products and 161 partner countries over the period 2008-2023.

Table 2: Summary statistics of manufacturing firm sample (avg. 2010-2021)

	Source	mean	std dev	5th perc	median	95th perc	N
Panel A: firms in business groups							
Employment	Fare	171	877	3	43	564	5,959
Output (,000)	Fare	58,175	730,800	0	7,013	145,900	5,959
Value Added (,000)	Fare	14,412	176,100	-28	1,953	36,324	5,959
Hourly Wage	Fare	21	11	14	19	31	5,959
Tangible assets (,000)	Fare	64,266	1,936,000	0	2,077	62,998	5,959
Equipment assets (,000)	Fare	48,099	1,533,000	0	855	37,892	5,959
Automation (,000)	Customs	189	5,525	0	0	130	5,959
Exports (,000)	Customs	9,062	110,990	0	0	23,192	5,959
Imports (,000)	Customs	5,164	60,077	0	0	15,725	5,959
Panel B: domestic firms							
Employment	Fare	10	140	0	3	28	620,525
Output (,000)	Fare	1,987	126,400	0	181	3,613	620,525
Value Added (,000)	Fare	469	13,861	-3	68	1,099	620,525
Hourly Wage	Fare	15	26	8	13	23	620,525
Tangible assets (,000)	Fare	879	47,424	0	35	1,083	620,525
Equipment assets (,000)	Fare	529	36,756	0	9	464	620,525
Automation (,000)	Customs	5	549	0	0	0	620,525
Exports (,000)	Customs	320	36,173	0	0	0	620,525
Imports (,000)	Customs	256	24,338	0	0	0	620,525

In Table 2, we report the summary statistics for the main firm-level variables used in this study, distinguishing between business group members and domestic firms. While the former group is relatively small, it mostly includes medium-large firms, which account for a large share of French workforce, tangible assets, and international trade.

3.4 Matched employer-employee data

We exploit a large employer-employee dataset provided by French Institut National de la Statistique et des Eťudes Ećonomiques (INSEE). La Base Tous Salariés (BTS-Postes or DADS-Postes) captures social security submissions for almost the entire population of French private sector employees (on average 28,000,000 workers per year), excluding individual employers and extraterritorial entities (classified under division 99 of the NAF rev. 2). It contains reliable worker-level information on gross annual income, total paid hours within the year, start and end dates of employment within the reporting period, employment status (either full-time or part-time), specific occupation (down to the 4-digit level), home municipality, gender, and birth year. Worker hourly wage is constructed using

DADS annual gross wage variable (salarié brut).[24] The hours worked variable is calculated by trimming the raw variable so that no worker works more than 1820 hours a year (equivalent to a full-time job in France) for each firm. Once hourly labour costs are computed, we drop worker who are found to earn less than 80% the minimum wage. Moreover, we drop all workers younger than 18 or older than 60, interns, self-employed, and the ones employed in public or semi-public companies.

Table 3: Summary statistics of manufacturing DADS sample (avg. 2010-2021)

	mean	**std dev**	**5th perc**	**median**	**95th perc**	**N**
Panel A: firms in business groups						
Male	0.64	0.23	1	1	0	1,020,567
Age	41	12	22	42	59	1,020,567
Working hours	1,599	515	434	1,820	2,200	1,020,567
Hourly Wage	24	63	11	18	39	1,020,567
Incumbent	1	0	0	1	1	1,020,567
Distance	38	99	1	11	180	1,020,567
Panel B: domestic firms						
Male	1	0	1	1	0	6,273,871
Age	40	12	20	40	59	6,273,871
Working hours	1,484	563	312	1,773	2,045	6,273,871
Hourly Wage	18	46	8	14	29	6,273,871
Incumbent	1	0	0	1	1	6,273,871
Distance	31	90	0	9	118	6,273,871

Each individual in the dataset is linked to a unique establishment identifier, and for those working at multiple locations within the same year, only the main occupation is considered in our analysis. The annual records for each year t provide job-level data for the preceding year $(t-1)$, forming a two-year panel at the job-level. For the purpose of this study, we consider only manufacturing workers and we compile a comprehensive matched employers-employees panel dataset spanning from 2010 to 2021, following the method outlined in Babet et al. (2022). Table 3 reports descriptive statistics for the main variables used in the study.

3.5 Task-content data

Task content proxies are built on the basis of data retrieved from the US Occupational Information Network (O*NET). The dataset provides information on the characteristics of nearly 900 occupations in its latest version. Each 4-digit ISCO88 occupation is measured

[24] Specifically, it includes: base salary, premiums, overtimes, reimbursements, severance benefits, amounts paid by third parties, actions and stock-options, holiday pay

in terms of 42 specific tasks. We first construct proxies for three dimensions of task content that are relevant for this study, namely routine cognitive task intensity, routine manual task intensity, and offshorability, as used by the relevant literature (D. Autor & Dorn, 2009; D. H. Autor & Dorn, 2013; D. H. Autor et al., 2003; Goos et al., 2009). The measures are then assigned to 4-digit PCS occupations using weights calculated on the basis of the 2010 US Census and the 2010 edition of the European Labour Force Survey (LFS).[25]

[25]We convert SOC2010 occupations into ISCO08 occupations using US employment weights and subsequently map ISCO08 occupations into the 4-digit PCS2003 occupations (French occupational classification) using the weights computed on the basis of the French Labour Force Survey. The procedure closely mirrors the one proposed by Le Barbanchon and Rizzotti, 2020

4 Descriptive Evidence

While the literature on the economic consequences of climate change has thoroughly investigated the negative effect of climate disasters on countries' economic output, long-term growth, physical and human capital, and firm performance (Burke et al., 2015; Hsiang & Kopp, 2018; Kahn et al., 2021; Pachauri et al., 2014; Somanathan et al., 2021), only a few recent studies have directly investigated the effect on inward foreign direct investment. Hence, before moving to the main empirical analysis, we need to test the relevance of natural disasters for the location of foreign activities of firms by leveraging the comprehensive microdata discussed above.

In this Section, we conduct a simple country-level analysis to test the ability of the shocks exploited in the analysis to affect the aggregate FDI stock and inflow in affected countries. We do this by examining the impact of natural disasters on the change in the net FDI position (the stock of foreign direct investment held at a specific point in time) of origin countries j in destination countries i.

Following Gu and Hale (2023), we define the dependent variable as:

$$\Delta FDI^k_{ij,t} = \frac{FDI^k_{ij,t} - FDI^k_{ij,t-1}}{\overline{FDI^k_{j,t-1}}} \tag{1}$$

where $FDI^k_{ij,t}$ is country j's FDI position in country i,[26] while $\overline{FDI^k_{j,t}}$ is the overall outward FDI position of country j in year t. The specification takes the following form:

$$\Delta FDI^k_{ijzt} = X'_{ijz,t-1}\beta_1 + ND^f_{ijz,t-1} + \psi_{ij} + \phi_{jt} + \rho_{zt} + \varepsilon_{ijzt} \tag{2}$$

The model includes country-pair fixed effects, ψ_{ij}, which account for unobservable time-invariant factors that might affect the evolution of FDI flows between two countries. Source country-year fixed effects, ϕ_{jt}, absorb the impact of any unobservable shock in the origin country that might affect its propensity to invest abroad. Finally, target country income

[26] UNCTAD defines Foreign Direct FDI position as the value of the stock of direct investment at a specific point in time. This stock represents the total accumulated value of foreign direct investments made by investors from one country in enterprises in another country, minus any disinvestments UNCTAD (2013).

group fixed effects,[27] ρ_{zt}, absorb the variation in FDI position common to similar countries in the region. Lastly, we include a set of time-varying macroeconomic variables.[28]

This analysis can only provide preliminary insights and cannot establish causal relationships. First, in the absence of industry-level data on FDI flows, it is not possible to account for sectoral confounders that may drive the overall effect. Moreover, even the availability of industry-country pair-level data would not suffice, since without information on the actual geographical extension of the shocks we are not able to identify the most affected sectors in the country. This is a common problem in this literature, which implicitly assumes that a single shock affects all firms in the country. Furthermore, data on FDI flows and positions do not necessarily capture the impact of natural disasters on reshoring decisions. Nevertheless, country-level data provide some preliminary insights into the macro-effects of natural disasters.

Table 4: Country pair-level analysis

Dep. Var.: Δ Inward FDI	(1)	(2)	(3)	(4)	(5)
Any disaster	-0.00653***	-0.00564***	0.00257*	-0.0111***	
	(0.00214)	(0.00211)	(0.00133)	(0.00367)	
Climatological					-0.00329***
					(0.00114)
Hydrological					-0.00444**
					(0.00177)
Meteorological					-0.00225
					(0.00159)
Observations	134,352	127,230	57,454	69,776	127,230
R-squared	0.107	0.107	0.107	0.123	0.107
Macroeconomic covariates		✓	✓	✓	✓
Country pair FE	✓	✓	✓	✓	✓
Origin country × Year FE	✓	✓	✓	✓	
Destination income group × Year FE	✓	✓	✓	✓	✓
Group	All	All	AE	EME/LIC	All

Notes: This table presents regression results of the model presented in Equation (2). The dependent variable is che relative change in the FDI position of origin country j in country i. Robust standard errors are clustered at the country-pair level and reported in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

[27] We use the standard UN classification that identifies advanced, emerging, and low-income economy.

[28] We include change in GDP, Trade-to-GDP ratio, CPI, and a set of dummies that equal one from the moment when the two parties sign a bilateral investment treaty (BIT), a treaty with investment provisions (TIP) or a regional trade agreement (RTA).

Table 4 reports the estimates of the model in Equation (2). Column (1) indicates that natural disasters reduce the FDI position in the affected country by 0.6% on average. In column (2), we show that the estimate is not driven by the main macroeconomic trends recorded in the destination country. In columns (3)-(4) we replicate the model focusing on different income groups. Interestingly, the effect appears mostly driven by emerging and low-income countries (EME/LIC), which report a 1.1% decline in the FDI position of investing countries, whereas the effect on advanced economies (AE) is slightly positive. Column (5) provides a breakdown by broad disaster categories, which shows that affect is mostly driven by climatological and hydrological hazards.

In Appendix C.1, we provide additional evidence by estimating a country-level regression that investigates the relationship between the net FDI flows as a share of GDP and various types of natural disasters. Results confirm a negative and significant relationship between natural disasters and inward FDI flows, with an average decline of 4.8% in FDI flows in the year following the event.

Overall, this preliminary evidence confirms the negative relationship between natural disasters and offshoring supported by the recent empirical literature (Carvalho and Grassi, 2019, C. E. Boehm et al., 2019, Dingel et al., 2019, Feyrer, 2021, Gu and Hale, 2023, Forslid and Sanctuary, 2023, Feng and Li, 2021). However, the establishment of a causal relationship between natural hazard and divestment necessitates a shift to firm-level analysis.

5 Empirical Analysis

This study explores the chain that links natural disasters, the divestment of foreign affiliates, and the propagation of the shock within the business group, with the final goal of shedding new light on the impact of shock-driven reshoring dynamics on automation and skill composition in parent firms.

In Section 5.1, we explore the direct effect of natural disasters on the divestment propensity of foreign subsidiaries. Besides the average effect, we study how the position of the firm within the business group affects the response to the shock. The baseline analysis is complemented by robustness exercises discussed in Annex C.2.

The decision to divest a plant in a territory hit by a natural disaster does not necessarily lead to the reshoring of foreign activity to the home country. The business group could choose to keep operating in the affected territory, establish a plant in a different region within the same country, or alternatively, relocate the investment to an entirely different country. In Section 5.2, we shift our focus to the entire business group to investigate whether the decision to divest from a region hit by a shock leads business groups to invest in other regions. Additional robustness checks are reported in Appendix C.3. To provide further evidence supporting our assumption that the divestment of a subsidiary leads, at least in some cases, to reshoring decisions, in Appendix C.4, we complement the analysis by investigating whether natural disasters affect the export of intermediate products from the country affected by the shock.

Having established the causal relationship between natural disasters and the divestment of foreign activities, we turn to examine the indirect effects on parent firms. To this end, we focus on France, where we have access to matched employer-employee data, alongside firm-level information on transactions and investment in automation. Furthermore, we restrict the analysis to foreign affiliates located in regions with a GDP per capita below that of France. This approach allows us to concentrate on shocks affecting foreign activities in countries that could potentially offer lower factor costs to parent firms. In Section 5.3.1, we investigate how exposure to a foreign shock affects firm-level outcomes. Specifically, the analysis explores the effects on intra-industry trade in intermediates, employment and investments in automation for firms operating in automation-intensive and non-automation intensive sectors. In Section 5.3.2, we focus on workers and study the contribution of foreign natural disasters to the evolution of within- and between-firm wage premia.

5.1 Natural disasters and foreign affiliates

In this section, we exploit the multilayer ownership network constructed using BVD Orbis data (see Section 3.2 for details about the procedure). Our goal is to shed new light on the effect of natural disasters on the divestment propensity of foreign subsidiaries. By doing so, we also investigate how this idiosyncratic shock varies across different firm- and group-level dimensions.

5.1.1 Econometric Framework

Our baseline specification models the divestment propensity of firms as a function of exposure to local natural shocks affecting the region where the subsidiary is located in $t-1$. We adopt a simple linear probability model, which offers the required flexibility in the design of the specification. The specification takes the following form:

$$Divest_{ijt} = X'_{i,t-1}\beta_1 + D'_{c_{it-1},c_{jt-1}}\beta_2 + \beta_3 ND_{it-1} + \gamma_i + \phi_{c_i,k_i,t} + \rho_{jt} + \varepsilon_{ijvt} \tag{3}$$

where $Divest_{ijt}$ is a dummy that equals one if the subsidiary i, controlled by the parent firm j, is divested in time t, $X'_{i,t-1}$ is a vector of time varying subsidiary firm-level characteristics recorded in $t-1$, $D'_{c_{it},c_{jt}}$ are country pair controls,[29] and ND_{it-1} is a dummy taking value of 1 if the region c_i, where the affiliate is located, experienced an adverse natural event in time $t-1$. In order to isolate the effect of natural disaster on the divestment propensity of subsidiary i, our model includes a rich set of fixed effects. Subsidiary

[29] The country pair variables included are the ones generally used in gravity models and were retrieved from CEPII, World Bank, WEO

fixed effects, γ_i, partial out the impact of time-fixed unobservable subsidiary-level characteristics that could affect divestment propensity.[30] Destination country-industry-year fixed effects, $\phi_{c_i,k_i,t}$, absorb shocks affecting all affiliates operating in the same industry and country. Lastly, parent firm-time fixed effects, ρ_{jt}, absorb all the variation associated with the parent firm. While the inclusion of this term significantly affects the sample size, it addresses concerns about possible omitted variable bias associated with the performance and the overall investment strategy of the business group.

We extend the baseline model by analysing four different dimensions of heterogeneity: the spatial distance between the parent firm and the affiliate, the ownership distance defined as the number of ownership links separating the two entities, the routine task intensity of the activity, and the group's historical risk exposure.

5.1.2 Empirical evidence

Table 5 presents our baseline subsidiary-level results. The results indicate that subsidiaries are more likely to be divested after they are impacted by a natural disaster. In column (1) we report the result of a simple two-way fixed effect model, which shows that idiosyncratic shocks affecting the region where the foreign affiliate operates significantly increase its probability to be divested by the parent firm. To control for local industrial trends, column (2) includes year-income group-macroregion-industry fixed effects.[31] The magnitude of the coefficient declines by 35%, but the effect remains negative and significant. Column (3) incorporates parent firm-year fixed effects, which absorb all variation associated with the global ultimate owner and the business group the affiliate belongs to. Since the analysis is conducted at the subsidiary level, this extension excludes from the estimating sample all BGs with a single foreign affiliate and significantly reduces the sample size. The inclusion of these terms significantly reduces the magnitude of the coefficients, but the estimates remain positive and statistically significant. In columns (4)-(5), we further extend the model

[30] This term also absorbs any time invariant institutional or economic characteristic of the location where the firm operates.

[31] Countries are divided based on three income groups (high-, middle- and low-income) and seven macroregions (South Asia, Europe & Central Asia, Middle East & North Africa, Sub-Saharan Africa, Latin America & Caribbean, East Asia & Pacific, North America), following the classifications provided by the World Bank.

to include time-varying subsidiary- and country pair-level characteristics.[32] These covariates concern some of the channels through which natural disasters affect the economy, but their inclusion helps to isolate the local effect of the shock. The coefficient for the natural disaster term remains largely unchanged. Finally, in column (6), we include destination country-industry-year fixed effects. This term absorbs all the country-level variation in divestment propensity and partially account for aggregate adjustments to the shock. The sensible increase in the magnitude of the coefficient suggests that public aid and other measures put in place to alleviate the consequence of the shock might produce short-run positive effects on business survival rate at the country level.

Table 5: Subsidiary-level Analysis

Dep. Var.: Divestment	(1)	(2)	(3)	(4)	(5)	(6)
Natural Disaster	0.0556***	0.0364***	0.0233***	0.0236***	0.0243***	0.0413***
	(0.0206)	(0.0112)	(0.00713)	(0.00750)	(0.00737)	(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×IncomeGroup×Region×Industry FE	-	✓	✓	✓	✓	-
Parent firm×year FE	-	-	✓	✓	✓	✓
Destination Country×Industry×Year FE	-	-	-	-	-	✓

Notes: This table presents regression results of the model presented in Equation (3). All specifications include subsidiary fixed effects. Columns (1)-(2) include parent country-year fixed effects. Columns (2)-(5) include income group-macroregion-industry-year fixed effects. This term is replaced in column (6) by destination country-industry-year fixed effects. Columns (3)-(6) include parent firm-year fixed effects. A complete list of subsidiary-level and control-level covariates is reported in Table A.2.2. Robust standard errors are clustered two-way by subsidiary firm and region and reported in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 6 analyses the heterogeneous impact of natural shocks with respect to key subsidiary-level characteristics. In column (1), we interact the main explanatory variable with a measure of the BG's historical exposure to natural disasters.[33] The estimates indicate, as expected, that less risk-averse business groups are less likely to divest an affiliate following a natural disaster. Column (2) reveals that the geographic distance between the parent and affiliate also shapes the effect of natural hazards: firms located further from the parent

[32] A complete list of the covariates is reported in Table A.2.2.

[33] We identify all regions where the BG was active at the start of the period and calculate the proportion of these regions that experienced natural disasters between 1990 and 2010.

company are more likely to be divested after a shock.

In Column (3), we observe a positive relationship between the magnitude of the effect and the degree of routine task intensity of the affiliate.[34] This finding suggests that firms with a higher concentration of automatable tasks are more prone to divestment.[35]

Table 6: Subsidiary-level Analysis - Heterogeneity

Dep. Var.: Divestment	(1)	(2)	(3)	(4)	(5)	(6)
Natural disaster	0.0602***	0.0410***	0.0392***		0.0268***	0.0980***
	(0.00901)	(0.00810)	(0.0086)		(0.00824)	(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

Notes: This table presents regression results of the model presented in Equation (3). All specifications include subsidiary, destination country-industry-year and parent firm-year fixed effects. The proxy for BG historic risk exposure is constructed as the pre-sample share of affiliates located in a territory hit by a natural disaster between 1990 and 2010. This industry-level routine task intensity index is obtained by aggregating the occupational routine intensity index, using weights retrieved from the 2010 European Labour Force Survey (LFS). '1st layer' affiliates are firms directly controlled by the parent firm, '2nd layer' firms are controlled through a single intermediary, whereas '3rd+ layer' firms are located further away from the centre of the network. Columns (1)-(4) cover the whole sample, whereas columns (5) and (6) only include firm located, respectively, in high-income and low/medium income countries. Robust standard errors are clustered two-way by subsidiary firm and region and reported in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

We then examine whether an affiliate's relative position within the business network influences its likelihood of divestment. In column (4), we differentiate between directly controlled firms (1st layer), firms controlled through a single intermediary (2nd layer), and firms further down in the business group hierarchy. Interestingly, we find a non-significant effect for directly controlled firms, while the average positive effect is mainly driven by firms positioned at different hierarchical levels within the ownership network. This result

[34] This measure is derived by aggregating the occupational routine intensity index, weighted based on data from the 2010 US Census and the 2010 European Labour Force Survey (LFS).

[35] In this regard, our result aligns with Faber et al. (2023), who find that uncertainty's positive impact on reshoring is driven by sectors where tasks are easily automated.

may reflect that the *routinisability* of subsidiary activities tends to increase with their hierarchical distance from the parent company (Altomonte et al., 2021). In columns (5) and (6) we separately replicate the model for advanced economies (HI) and low/medium income countries (LMI). The results are consistent, but the magnitude of the coefficients appears significantly higher for the second group.

Overall, the analysis points to a significant positive effect of natural disasters on the likelihood of divestment. However, this effect appears to be concentrated among firms located at the geographical and organisational periphery of the group.

In the baseline model presented in equation (3), the main explanatory variable is a simple dummy which identifies the occurrence of large natural disasters as defined in section 3.1. In Appendix C.2, we replicate the model by accounting for the intensity and the nature of the disaster. In Table C2, we replicate the analysis using a proxy for disaster intensity, which corresponds to the ratio between disaster damages and the GDP recorded by the country the previous year. Results are broadly in line with the baseline model. In Table C3, we present a breakdown of the shock by disaster type. Although all three categories show positive and significant coefficients, the magnitude for climatological disasters is found to be twice as large as that for hydrological and meteorological disasters.

The causal identification of the effect of natural disasters on firm divestment propensity relies on the assumption that the shocks can be considered as-good-as-random. On this regard, there are two main identification challenges. First, firm selection might affect the results. More risk-averse BG, which could be more open to invest in risky regions, may be more likely to divest their affiliates. Second, the intensity of the shock could be associated with time-varying economic characteristics of the region which make it both more vulnerable to exogenous event and less suitable to host foreign-owned firms. To address these challenges, in Table C4 we exclude all regions which recorded any type of natural disaster between 1990 and 2010. The exclusion of a large number of territories interacts with the restrictive set of fixed effects included in the model,[36] leading to a 70% reduction in sample size. Nevertheless, the estimates appear surprisingly in line with the results presented in the main analysis.

[36]In particular, by reducing the geographical extension of the analysis, we increase the share of business groups with only one subsidiary in the sample, which are absorbed by parent firm-year fixed effects.

5.2 Propagation through global ownership networks

The analysis presented in section 5.1 provides evidence of the effect of natural disasters on foreign affiliates. However, these results could be consistent with a simple reallocation of economic activity across different foreign territories. In this Section we focus on the whole business group, to understand whether divestment episodes driven by idiosyncratic shocks are entirely compensated by the simultaneous opening of new affiliates in the same country or elsewhere.

5.2.1 Econometric Framework

The empirical framework investigates the relationship between the business group's exposure to an idiosyncratic shock through one or more foreign affiliates and the subsequent change in the composition of foreign assets. The specification takes the following form:

$$\Delta Naff_{jt} = X'_{j,t-1}\beta_1 + \beta_2 ND_{jt-1} + \gamma_j + \lambda_{c_j t} + \varepsilon_{jt} \tag{4}$$

where $\Delta Naff_{jt}$ is the change in the number of foreign affiliates between t and $t-1$, $X'_{j,t-1}$ is a time varying vector of business group-level characteristics and ND_{jt} is a dummy that equals one if one of the affiliates of the business group is hit by a shock. In order to isolate the effect of natural disaster on the structure of business groups, our model includes business group fixed effects, γ_j, which partial out the impact of time invariant unobservable group characteristics, and parent firm country-year fixed effects, $\lambda_{c_j t}$, that absorb parent country-level shocks.

5.2.2 Empirical evidence

Table 7 presents the estimates of the model specified in Equation (4), incorporating both business group and year fixed effects. The estimates presented in column (1) reveal a negative and significant impact of exposure to natural disasters on the size of business groups.

In column (2), we include origin-country-year fixed effects to control for country-specific common shocks affecting the parent firm. The estimates remain unchanged. Column (3) focuses on large business groups, defined as those comprising five or more foreign affiliates. In this case, the magnitude of the effect increases by 40%, suggesting that larger multinational groups may exhibit greater responsiveness to such shocks. In column (4), we test the predictions of Grossman et al. (2023), examining whether business groups with parent firms located in relatively safer countries[37] are more likely to reduce their foreign exposure in response to an unexpected shock. Consistent with these predictions, we observe a 12% increase in the magnitude of the effect. Finally, column (5) demonstrates that the results hold even when restricting the sample to business groups led by France-based parent firms. Overall, these findings confirm that natural disasters adversely affect the structure of business groups.

Table 7: Business group-level analysis

Dep var.: Δ Affiliates	(1)	(2)	(3)	(4)	(5)
Natural Disasters	-0.109***	-0.106***	-0.144***	-0.122***	-0.114***
	(0.0121)	(0.00963)	(0.0239)	(0.0207)	(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×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

Notes: This table presents regression results of the model presented in Equation (4). All specifications include business group and year fixed effects. In column (2)-(5) the specification incudes home country-year fixed effects. Estimates presented in column (3) refer to business groups with at least 5 subsidiaries at the beginning of the period. Column (4) focus on business group whose parent firm is located in a safe country. Column (5) includes only business groups led by a France based firm. Robust standard errors are clustered at the parent firm-level and reported in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

In Table 8 we further investigate the way business groups react to a shock to one or more of their affiliates. In the first panel, we focus on 1-layer business groups, namely

[37] We assess countries' exposure to natural hazards based on the ND-GAIN score developed by the Notre Dame Global Adaptation Initiative (Chen et al., 2015). We identify safe countries as those with an ND-GAIN score above the median.

groups where all subsidiaries are directly controlled by the parent firm. A natural disaster is associated with a 6.4% standard deviation decrease in the growth of the group. In Panel B are report the estimates for BGs with up to 2 degrees of separation between the HQ and the corresponding affiliates. For this type of BG, a natural disaster is associated with a 7.4% standard deviation decline in the evolution of the group. The negative effect is found to be slightly larger for firms in the first layer.

Table 8: Business group-level analysis - Heterogeneity

VARIABLES	(1) Δ Affiliates	(2) Δ Affiliates (1st layer)	(3) Δ Affiliates (2nd layer)	(4) 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***	-0.113***	-0.0984***	
	(0.00540)	(0.0108)	(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***	-0.0700***	-0.152***	-0.116***
	(0.0206)	(0.0189)	(0.0276)	(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 × Year FE	✓	✓	✓	✓

Notes: This table presents regression results of the model presented in Equation (4). All columns include business group and parent firm country-year fixed effects. Robust standard errors are clustered at the parent firm-level and reported in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Finally, in Panel C, we report the estimates for complex business groups comprising more than 2 layers. In this case, a natural disaster leads on average to a 15% standard deviation decrease in the number of foreign affiliates. The effect is negative and significant for all layers, with a significantly higher magnitude for firms in the second layer.

Overall, these results suggest that natural disasters can lead to important changes in the internal structure of international business groups. However, we are not able to observe directly whether these changes translate into the backshoring of economic activities. To support this claim, in Appendix, Section C.2, we conduct a different exercise, focusing on France. By exploiting firm-level transaction data, we show that natural disasters lead to a sizeable decrease in firm-level imports from the affected country. This is true even when we focus on intra-industry trade in intermediates, a specific kind of trade that has been defined by the literature as 'narrow offshoring' (Feenstra & Hanson, 2003; Hummels et al., 2014).[38]

The model presented in Equation 4 is subject to the same identification challenges as the subsidiary-level one, namely the possibility of firm sorting and the endogenous effects of disasters. To address these concerns, in Table C5, we replace our proxy for exposure to natural disaster intensity with a measure of 'excess disaster', which disregards disasters occurring in areas already affected by a natural hazard during the period 1990–2010. The estimates largely confirm the results presented in Table 7.

In Figure C1, we compute an event study using the robust DID estimators developed by De Chaisemartin and d'Haultfoeuille (2024). Reassuringly, we do not find evidence of pre-trends in business group growth before the shock.

[38] The intra-industry trade in intermediates involves products that the parent firm could potentially produce at home. For this reason, the literature uses trade flows involving this inputs as a proxy for offshoring

5.3 Effects on domestic skill composition and investments in automation

Anecdotal evidence suggests that the divestment of one or more subsidiaries in the parent's global value network can lead to a reallocation of economic towards the parent's home country. While a few studies have documented the extension and main properties of backshoring dynamics, the literature has so far struggled to quantify the real dimension of these phenomena and the relative drivers. Notably, there is still no consensus on how these dynamics affect domestic wage distributions and within- and between-firm inequalities.

In this section, we leverage exogenous shocks to foreign affiliates to causally identify their indirect effect on parent firms. We focus our analysis on France, using a panel matched employer-employee dataset covering the entire population of private sector workers, as well as firm balance sheet data. Moreover, we consider only the exposure to regions where the parent firm could have potentially accessed low-cost unskilled labour.

To study how shocks to foreign affiliates affect domestic firms in France, we develop a measure of the group's exposure to the local shock. The variable is constructed by weighting the shock dummy, ND_{it}, for each subsidiary i in time t by the share of this subsidiary in the overall BG j's foreign employment in pre-sample period:

$$\overline{WT}_{jt} = \sum_i ND_{ijt} * \frac{L_{ijt-n}}{L_{jt-n}} \tag{5}$$

While all manufacturing sectors are exposed to foreign natural disasters, firms' ability to respond to the shock is constrained by the efficiency of automation technologies characterising their sector. In order to account for this dimension, we separately replicate our baseline models focusing on firms belonging to two groups, broadly defined as 'automation-intensive sectors' and 'non-automation intensive sectors'.[39]

[39] In line with the literature, we define robot intensive industries as the ones with a ratio of 1 robot per 10,000 employees or more.

5.3.1 Firm-level analysis

In this section, we focus on firm-level outcomes. For our analysis, we consider 'parent firms' to include not only the French global ultimate owner, often a holding company, but also all directly controlled domestic affiliates located in France. This approach enables us to select a large sample of manufacturing firms that (1) are located in France and (2) are central to the business network. Table A2 presents a selection of statistics for firms in this group compared to the entire manufacturing sector. Only 1% of manufacturing groups have foreign affiliates, yet these firms account for 18% of total employment, 22% of exports and 47% of the equipment assets. These firms typically pay higher wages and are more likely to invest in broad automation technologies and industrial robots (Leone, 2023).

Our primary goal is to assess how exposure to natural disasters impacts firm structure and investments in automation. This includes changes in a firm's stock of automation technologies and the transition to 'robot adopter' status. We propose two different proxies for these types of investment. The first, which we define as 'machinery', is the firm-level investment in 'Machinery, equipment and tools' retrieved from the FARE dataset. This variable covers all investments in equipment, but might include products that fall beyond our definition of automation technologies. The second, which we define as 'automation', is the sum of the imports of capital products belonging to two broad groups of automation technologies.[40] In line with the literature (Acemoglu et al., 2023), we define firms as "robot adopters" starting from the first time they invest in industrial robots ('automation') in an amount equal to or greater than the median investment reported by firms purchasing this technology.[41]

[40] See section B.1.3 for more details

[41] By focusing on manufacturing firms belonging to large business group only, we identify a threshold of €2,500 (see Section B.1.3).

5.3.1.1 Econometric Framework

Our firm-level specification takes the following form:

$$\ln Y_{jt} = X'_{jt}\beta_1 + \beta_2 \overline{WT}_{j,t-1} + \gamma_j + \psi_{kt} + e_{jt} \tag{6}$$

where Y_{jt} is an outcome recorded by firm j, in time t, X_{jt} is a vector of time-variant firm j characteristics. The model includes firm fixed effects γ_j, which partial out the impact of time invariant unobservable firm characteristics, and industry-year fixed effects, ψ_{kt}, which control for industry-specific shocks.

5.3.1.2 Empirical evidence

In Table 9, we estimate the effects of exposure to natural disasters on firm performance. In column (1) we record a non-significant positive effect on employment. In column (2), when we include industry-year fixed effect, the effect becomes significant, but remains quite small in magnitude. A shock hitting all foreign affiliates of the business group increased domestic employment by a 0.5%. This effect appears to be mostly driven by automation-intensive sectors. In columns (3) and (4) we turn our focus to intra-industry imports of intermediates ('narrow offshoring')[42]. Consistently with the findings reported in Table C6, we find that natural disasters negatively affect narrow offshoring flows. When we control for industry-specific shocks, the exposure to a foreign disaster is associated with a 3% decline in intermediate inputs. However, the effect seems entirely driven by sectors that are not automation-intensive. This result is in line with the predictions of Artuc et al. (2023), which suggest that the productivity effects associated with automation increase the demand for non-automatable foreign inputs to the point of offsetting any displacement effect in the foreign country. Finally, in columns (5) and (6) we assess the effect of the shock on investments in machinery.[43] We find that natural disasters lead on average to a 5.9%

[42] In this specification, we consider total intra-industry imports of intermediates, including both affected and unaffected partner countries.

[43] The proxy, retrieved from the FARE dataset, includes all investments in 'Machinery, equipment and tools' (*AR - Installations techniques, matériel et outillage industriel*)

increase in investments, largely driven by automation-intensive sectors, where automation is economically feasible.

A common concern with this class of shift-share variables is that the exposure to the shocks may not be random. For instance, firms experiencing rapid growth may have disproportionately invested in risk-prone regions in prior years, introducing bias into the results. To address this issue, we employ the methodology proposed by Borusyak and Hull (2023). This approach involves incorporating a proxy for 'expected exposure' into the specification. The proxy is constructed by simulating 1,000 counterfactual sets of natural disasters and averaging the resulting counterfactual shocks, thereby controlling for potential non-random exposure to the shocks.

Table 9: Firm-level outcomes

	(1) Employment	(2) Employment	(3) Intermediates	(4) Intermediates	(5) Machinery	(6) Machinery
			All			
Disaster exposure	0.00373	0.00515**	-0.0264*	-0.0309**	0.0515**	0.0589**
	(0.00245)	(0.0025)	(0.0135)	(0.0137)	(0.0227)	(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
			Automation-intensive sectors			
Disaster exposure	0.00511	0.00663**	-0.00589	-0.00661	0.0709**	0.0785**
	(0.00324)	(0.00334)	(0.0212)	(0.0215)	(0.0302)	(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	0.0032	-0.0539***	-0.0639***	0.0231	0.0281
	(0.00373)	(0.00362)	(0.0132)	(0.0137)	(0.0347)	(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	-	✓	-	✓	-	✓

Notes: This table presents regression results of the model presented in Equation (6). The measure of exposure to natural disasters is presented in Equation (5). All specifications include firm fixed effects. Specifications in columns (1), (3), and (5) include year fixed effects, whereas the ones presented in columns (2), (4), and (6) include 4-digit industry-year fixed effects. Robust standard errors are two-way clustered at the firm- and business group-level and reported in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

The estimates are presented in Table C7. Reassuringly, the results are largely consistent with our main findings. In columns (1) and (2), we observe a further reduction in the magnitude of the effect on employment, which becomes statistically insignificant for the overall population. However, the negative impact on intra-trade imports and the positive effect on investment in machinery remain broadly confirmed.

In Table 10, we explore the effect of natural disasters on investment in automation technologies.[44] Column (1) shows a positive and significant effect of foreign shocks on the likelihood of investing in automation. The same result is confirmed in column (2), where we include firm and industry-year fixed effects. In column (3) we replicate the analysis focusing only on firms belonging to robot-intensive industries. The estimates are slightly higher in magnitude, although less significant. In columns (4) we instead focus on manufacturing industries that are not robot intensive. In this case, the magnitude of the coefficient is noticeably lower, and the effect is no longer significant.

Table 10: Robot adopters

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

Notes: This table presents the estimates of a simple linear probability model. A firm becomes robot adopter from the first time that it invests at least €2,500 in industrial robots. The measure of exposure to natural disasters is presented in Equation (5). Specifications reported in columns (2)-(4) include firm and industry-year fixed effects. Robust standard errors are two-way clustered at the firm- and business group-level and reported in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

This analysis confirms a small significant effect of natural disasters on robot adoption in the immediate aftermath of the shock. However, this result could be explained by the fact that firms whose affiliates are more exposed to natural disasters were already on differential trends relative to those with low exposures. We address this concern, using the

[44]See Appendix B.1.3 for details on the construction of the proxy.

robust estimators introduced by De Chaisemartin and d'Haultfoeuille (2024). This estimator, compared to others proposed in the literature, accommodates both multiple treatments over time and a non-binary treatment variable. For this reason, it appears particularly useful in the context of this analysis. The results are reported in Figure 2.

Figure 2: Robot adoption - Event study

(a) All manufacturing

(b) Breakdown by robot intensity

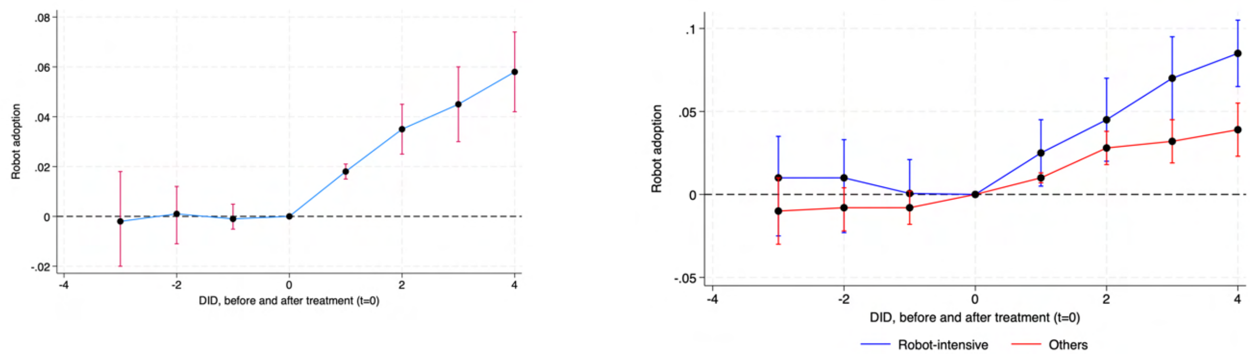


Figure (a) shows the effect on the whole manufacturing sector. We do not find any evidence of pre-trend. On the contrary, the probability to invest in industrial robots progressively increases after the shock compared to non-affected firms. In Figure (b) we distinguish between firms in robot-intensive industries and firms in low-automated sectors. The estimates confirm that the propensity to adopt automation technologies increase faster for firms belonging to the former group. However, the effect is sizeable for both, and we do not find any evidence of pre-trends.

5.3.2 Worker-level analysis

The firm-level analysis does not allow us to distinguish changes in skill-composition from direct effects on firm-level outcomes. Hence, it is not informative about the direct effect of foreign natural disasters on worker wages, nor it does provide any indication about the occupational heterogeneity of these effects.

In this Section we exploit the richness of our matched employer employee dataset to analyse the wage effect of these shocks across workers employed in different occupations, firms, and industries.

5.3.2.1 Econometric Framework

To isolate the effect of foreign shocks on the domestic workforce, we estimate a worker-level Mincer regression, where worker ν's log hourly wage is expressed as a function of time-variant worker-level and firm-level characteristics, respectively $X_{\nu t}$ and X_{jt}.

$$\ln HourlyWage_{\nu jt} = \beta_1 X_{\nu t} + \beta_2 X_{jt} + \beta_3 \overline{WT}_{j,t-1} + \gamma_\nu + \lambda_j + \psi_{kt} + e_{\nu jt} \tag{7}$$

The model includes worker fixed effects γ_ν, which partial out the impact of time-fixed unobservable individual characteristics, firm fixed effects, λ_j, which control for unobservable firm and business group-level characteristics, as well as industry-year fixed effects, ψ_{kt}, which account for industry-specific shocks.

By exploiting information on each worker's 4-digit occupational category, we can explore the heterogeneous effect of foreign shocks in terms of task content. We classify as 'directly affected workers' all blue-collar workers engaged in highly (manual or cognitive) routine tasks that could be easily replaced by industrial robots. Following a recent literature (Acemoglu et al., 2020, D. H. Autor and Dorn, 2013, Koster and Ozgen, 2021), we construct a routine task intensity index based on information provided by O*NET Online codes. We aggregate the measure at the 4-digit PCS[45] level using weights obtained from

[45]The nomenclature of occupations and socio-professional categories (PCS) is an occupational classification developed by the French Institute for Statistics.

the Labour Force Survey.[46] We then interact the main variable of interest with a proxy for occupation-level exposure to automation.

5.3.2.2 Empirical evidence

In the first column of Table 11, we estimate the effect of indirect exposure to natural disasters on workers' hourly wages. Estimates point to a 6% standard deviation increase in wage in response to a shock affecting all foreign affiliates. In column (2), we interact the main variable of interest with a proxy for routine task intensity. Our estimates show that the positive effect of the shock is reduced by one third for workers with routine intensity one standard deviation above the mean.

In columns (3) and (4), we replicate the two specifications focusing on robot-intensive industries, defined as sectors with an average of at least one industrial robot per 1,000 employees. Here, the magnitude of all coefficients is significantly higher. A shock affecting all foreign affiliates is associated with a 7% increase in wages. Once again, the effect is stronger for workers in non-routine task-intensive occupations. Finally, in columns (5) and (6), we replicate the analysis for industries with a limited presence of industrial robots. In this case, the average effect is negligible and non-significant. Moreover, workers with routine cognitive intensity one standard deviation above the mean experience a net negative effect.

Overall, these results confirm that shock-driven reshoring decisions have heterogeneous effects on the domestic workforce. The average positive effect is concentrated in robot-intensive industries and driven by non-routine occupations. These results are consistent with those presented in Table 10. In robot-intensive industries, firms hit by a natural disaster in their foreign affiliates tend to replace foreign activities with domestic automation technologies. These technologies foster higher average workers' wages and within-firm income disparities. Conversely, in industries where automation technologies are not yet widely spread, the adoption of automation technologies is less frequent and the effect on wages is negligible.

[46] See Section 3.5 for further details

As with the firm-level analysis, there is a concern that exposure to shocks may not be random. To address this issue, we replicate the analysis in Table C8, incorporating the 'expected exposure' into the specification. Reassuringly, the results are nearly identical, reinforcing their robustness.

Table 11: Worker-level Analysis

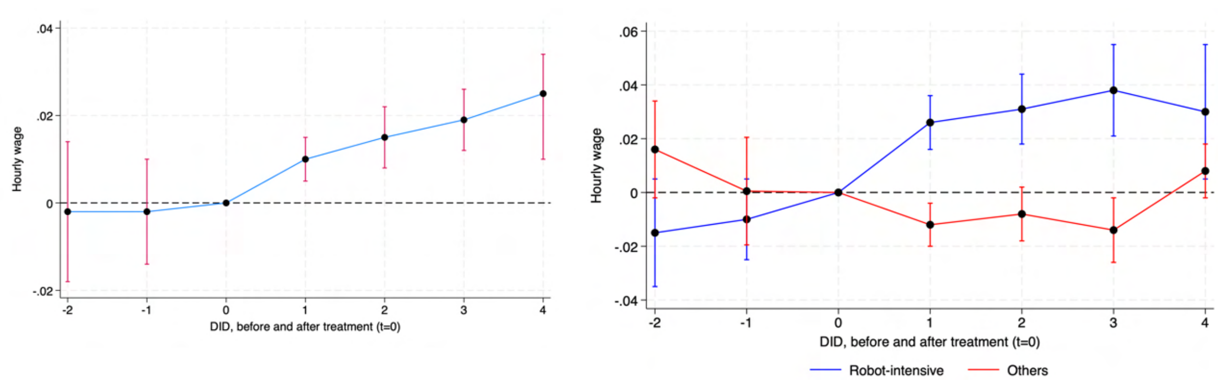
Dep var.	Hourly Wage					
	All manufacturing		Robot-intensive industries		Other industries	
	(1)	(2)	(3)	(4)	(5)	(6)
Natural disasters	0.0596**	0.0668**	0.0706**	0.0796**	0.0131	0.0163
	(0.025)	(0.0261)	(0.029)	(0.0305)	(0.0141)	(0.0144)
Routine cognitive		-0.0177***		-0.0169***		-0.0186***
		(0.0024)		(0.003)		(0.00388)
Natural disasters x Routine cognitive		-0.0281***		-0.0332***		-0.0175*
		(0.0096)		(0.009)		(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×industry FE	✓	✓	✓	✓	✓	✓

Notes: This table presents regression results of the model presented in Equation (7). The measure of cognitive task intensity is constructed using O*NET data, as discussed in Section 3.5. Robust standard errors are two-way clustered at the worker and parent firm-level and reported in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Figure 3: Effect on wages - event study

(a) All manufacturing

(b) Breakdown by robot intensity



In Table 3, we perform an event study using the robust estimators developed by De Chaisemartin and d'Haultfoeuille (2024). Reassuringly, the results of our TWFE model are largely confirmed and we find no evidence of pre-trends. Overall, the results at the firm and worker levels indicate that exposure to foreign natural disasters impacts domestic firms. While we observe an increase in investments in automation technology and upward pressure on wages in automation-intensive industries, no significant effects are found for other sectors. Conversely, non-automation-intensive industries tend to reduce their import of intermediate goods within the same industry ("narrow offshoring"). This effect might be offset in automation-intensive industries by the productivity effect driven by the adoption of a new technology. These findings support the hypothesis the partial substitution of foreign workers with domestic machines, occurring in industries where such a shift is technologically feasible.

6 Conclusions

In this paper, we shed new light on the propagation of idiosyncratic shocks within international ownership networks and on their effects on employment and automation in the parent firms. By combining detailed data on natural disaster occurrences with a comprehensive dataset encompassing over 8 million foreign affiliates, we identify the subsidiaries impacted by specific shocks within the study period. Unlike most previous studies that concentrate solely on firms directly controlled by the parent company, we examine these shocks within the broader framework of complex, multilayered business groups. We then extend these shocks to parent firms in France to explore the impact of foreign natural disasters on firms and workers in the home country. This approach enables us to analyse the automation-reshoring nexus from the perspective of a sudden decrease in the opportunity cost of investing in technology.

Overall, our results underscore the significant impact of local shocks on international business groups. Specifically, foreign affiliates affected by natural disasters exhibit a higher likelihood of divestment in subsequent years. However, this overall positive effect conceals substantial variation among different firm types. Foreign affiliates directly exposed to such exogenous shocks are more prone to divestment, particularly when the physical and ownership distances from the parent firm are greater.

Focusing on parent firms, we find that reshoring positively affects domestic employment and investments in automation. However, this overall positive effect conceals significant heterogeneity across different industries and occupational groups. First, the positive impact is entirely driven by automation-intensive industries. Furthermore, even within these sectors, there are notable differences between routine and non-routine intensive occupations, with non-routine occupations benefiting the most. This pattern is consistent with a partial substitution of low-skilled labour abroad with domestic automation, thereby boosting demand for high-skilled workers.

Taken together, these findings confirm that a firm's decision to reshore, particularly in response to an exogenous shock, is unlikely to restore the prior status quo. Instead, as parent firms repatriate specific tasks, they often restructure their production processes, invest in automation, and increase demand for occupations that were never exposed to the risk of offshoring.

Our findings have important policy implications for both advanced and emerging economies. In the face of an increasingly volatile global economy, marked by frequent natural and geopolitical shocks, it is crucial to establish specialised financial instruments aimed at supporting FDI recovery in emerging and low-income countries after disasters. The outflow of foreign capital, as revealed by our results, compounds the direct capital losses cause by such disasters. Financial mechanisms, inspired by initiatives like the World Bank's Catastrophe Bonds and other disaster-linked securities, could serve as effective models. Moreover, all countries, particularly those that are less developed, should enhance disaster preparedness and recovery plans to sustain investor confidence and reduce the risk of FDI withdrawal from vulnerable regions. Investment Promotion Agencies can play a pivotal role in this effort.

For developed nations, our findings underscore the need to adapt educational and vocational training programs to focus on non-routine and cognitive skills, fostering a workforce that is more resilient to technological and economic disruptions. The EU's *New Skills Agenda*, for instance, offers a strong framework for such adaptations. In sectors that are negatively impacted by automation, comprehensive transition strategies—including retraining programs, sectoral realignment, and economic diversification—are essential. Successful examples, such as Germany's *Kurzarbeit* scheme during periods of economic change, provide valuable lessons for managing these challenges effectively.

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A Data Appendix

A.1 Additional Figures

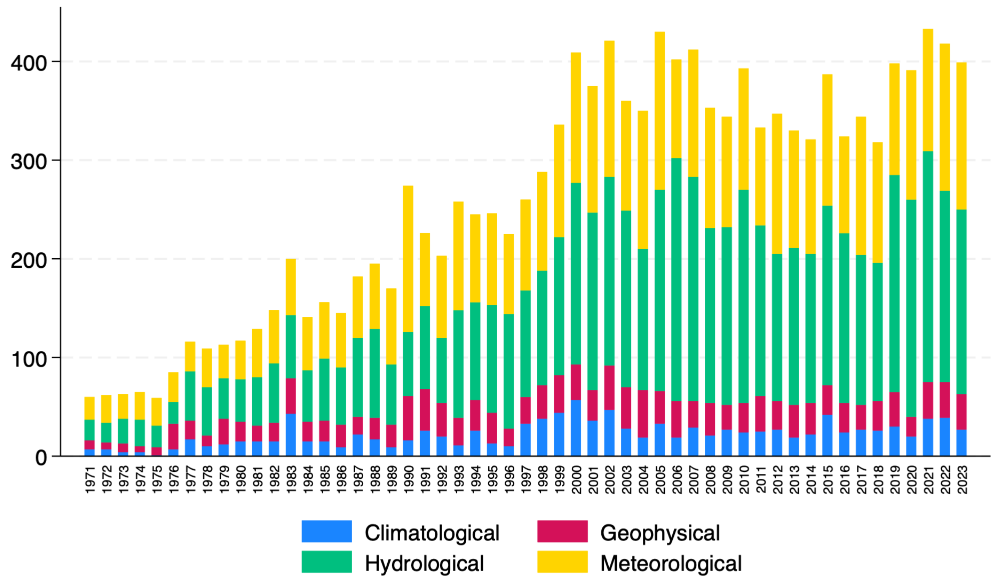
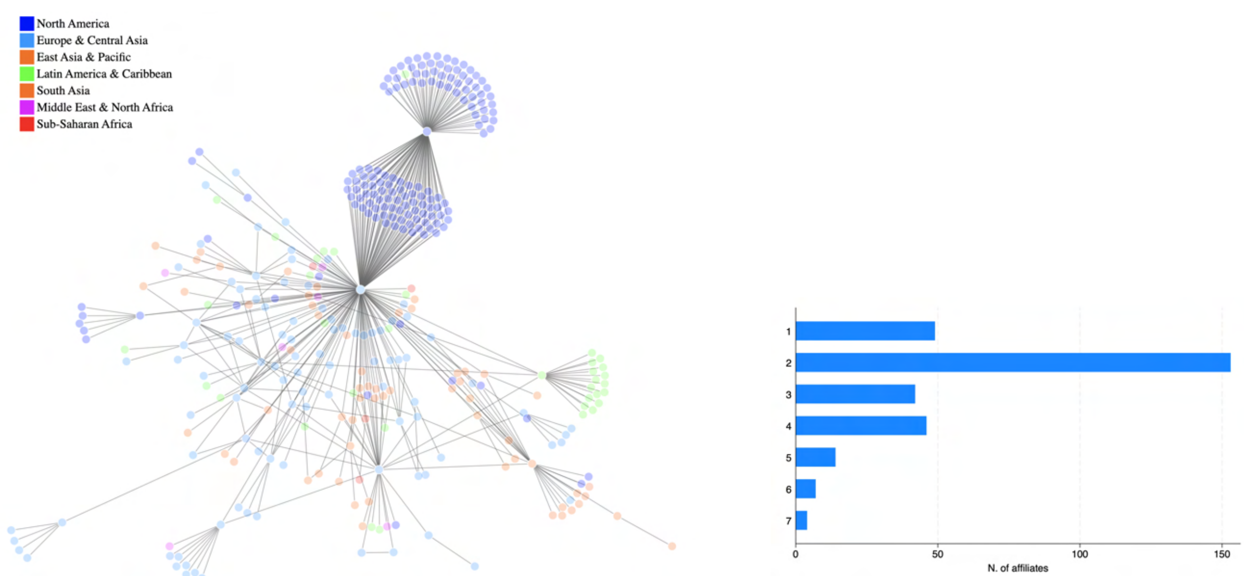


Figure A1: Disaster breakdown



(a) Ownership network (b) Hierarchical layers

Figure A2: Ownership network around an anonymous manufacturing firm

A.2 Additional data

A.2.1 International Federation of Robotics

The International Federation of Robotics (IFR) is an international association that groups leaders in the industry and selected research institutes in the field of robotics. The data provided by the IFR comes from voluntary submissions by individual manufacturers or national industry groups, primarily to keep its members updated on broader industry and market developments. Each year, the IFR gathers information on the installation of industrial robots worldwide for its World Robotics Reports (IFR, 2022) through two distinct surveys: one detailing annual installations by country and application, and the other by country and customer industry.

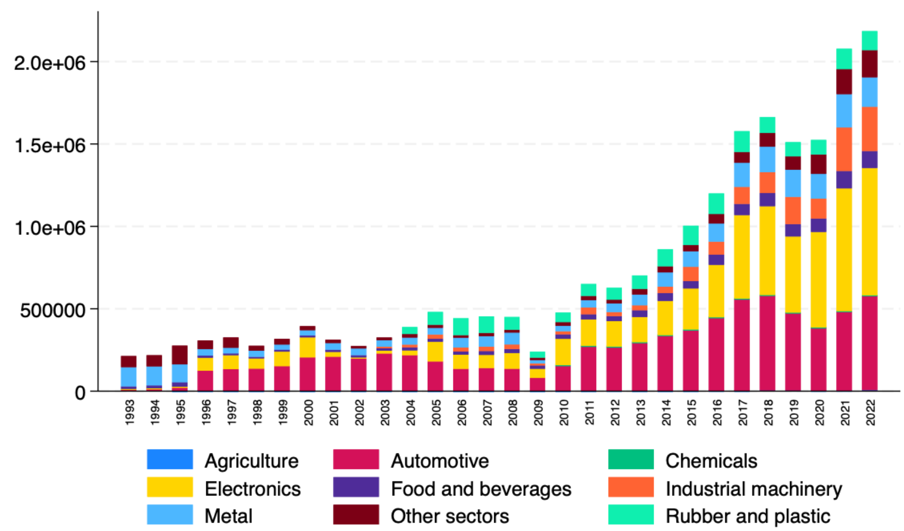


Figure A3: Robots by industry

Figure A3 gives an idea of the astonishing rise of these technologies over the last two decades. Despite the disruption created by the global pandemic and the geopolitical challenges that characterised the last decade, the sector recorded a 7% year-on-year unit sales compounded annual growth over the period 2017-2022 and is expected to keep this pace over the period 2023-2026. In 2021, the manufacturing sector counted 151 robots per 10,000 employees globally. In recent years, the trend has been particularly driven by automotive, electronics and metal industries. However, plastics and chemical industry as well as food and beverage also reported a solid growth (IFR, 2022, 2023).

A.2.2 Country-level data

Country and bilateral country level data are retrieved from different sources. In Tables A1, we report the main country- and country pair-level variables used in the analysis.

Table A1: Country-level data

Variable	**Source**	**Country-level**	**Country-pair level**
Annual/quartely GDP	IFS, OECD, World Bank	✓	
Monthly exchange rate	IFS, OECD, World Bank	✓	
Monthly GDP	Own calculation	✓	
RER Volatility	Own calculation	✓	
Trade to GDP	WTO	✓	
Taxes	World Bank's World Development Indicators	✓	
Quality of infrastructures	WEF Competitiveness Index	✓	
Political stability	World Bank's Worldwide Governance Indicators	✓	
Rule of law	World Bank's Worldwide Governance Indicators	✓	
Education	WEF Competitiveness Index	✓	
Inflation	WTO	✓	
Financial Development	World Bank's World Development Indicators	✓	
Entry costs	World Bank's World Development Indicators	✓	
Contract enforcement	World Bank's World Development Indicators	✓	
Profit tax	World Bank's World Development Indicators	✓	
Distance	CEPII		✓
Contiguity	CEPII		✓
Common language	CEPII		✓
Common ethnical origin	CEPII		✓
common currency	CEPII		✓
common legal origin	CEPII		✓
Bilateral investment treaty	UNCTAD		✓
Treaty with investment provision	UNCTAD		✓
Regional trade agreement	CEPII		✓

A.3 Summary Statistics

Table A2: Summary statistics

na38	label	Tangible Assets (,000)	Equipment Assets (,000)	Output (,000)	Value Added (,000)	Employment (,000)	Labour Cost (,000)	Exports (,000)	Imports (,000)	Automation (,000)	N. Firms
BZ	Industries extractives	3,032,043	2,150,000	2,193,000	713,000	6	246,700	5,636	8,493	87	187.6
CA	Fabrication de denrées alimentaires, de boissons et de produits à base de tabac	20,372,700	12,800,000	48,730,000	8,070,000	94	3,495,000	5,262,000	2,246,000	5,005	500.4
CB	Fabrication de textiles, industries de l'habillement, industrie du cuir et de la chaussure	1,321,566	672,000	3,758,000	1,040,000	17	587,800	1,255,000	1,290,000	3,193	191.6
CC	Travail du bois, industries du papier et imprimerie	2,940,937	2,090,000	3,978,000	1,070,000	15	549,100	855,000	618,300	2,606	216.4
CD	Cokéfaction et raffinage	579,086	413,000	2,953,000	294,000	2	97,199	301,400	162,900	100	15.1
CE	Industrie chimique	26,832,800	21,000,000	20,820,000	4,290,000	41	2,091,000	7,154,000	2,764,000	7,939	211.1
CF	Industrie pharmaceutique	4,475,109	2,530,000	7,282,000	1,930,000	15	825,900	4,135,000	1,415,000	13,500	40.9
CG	Fabrication de produits en caoutchouc et en plastique ainsi que d'autres produits minéraux non métalliques	11,623,500	7,590,000	17,820,000	5,420,000	68	2,763,000	4,140,000	3,141,000	61,200	481.0
CH	Métallurgie et fabrication de produits métalliques à l'exception des machines et des équipements	9,179,570	6,070,000	15,670,000	4,550,000	62	2,440,000	4,220,000	2,803,000	44,800	607.5
CI	Fabrication de produits informatiques, électroniques et optiques	2,963,268	1,780,000	10,840,000	4,180,000	40	2,160,000	4,292,000	1,856,000	514,000	160.8
CJ	Fabrication d'équipements électriques	2,598,721	1,730,000	7,320,000	1,730,000	23	976,600	2,716,000	2,289,000	115,000	120.6
CK	Fabrication de machines et équipements n.c.a.	2,468,066	1,280,000	9,015,000	2,400,000	31	1,339,000	3,499,000	1,494,000	62,800	249.5
CL	Fabrication de matériels de transport	10,744,500	6,300,000	30,460,000	8,170,000	80	3,989,000	13,570,000	7,508,000	128,000	163.9
CM	Autres industries manufacturières ; réparation et installation de machines et d'équipements	2,502,354	1,450,000	7,592,000	2,500,000	36	1,376,000	1,436,000	1,274,000	36,400	320.5
DZ	Production et distribution d'électricité, de gaz, de vapeur et d'air conditionné	266,556,000	212,000,000	100,600,000	25,100,000	70	3,996,000	177,800	803,200	1,382	338.5
EZ	Production et distribution d'eau ; assainissement, gestion des déchets et dépollution	5,634,715	2,520,000	9,691,000	2,920,000	41	1,508,000	360,400	66,242	4,052	298.3
FZ	Construction	8,269,543	3,470,000	39,220,000	10,100,000	155	6,404,000	360,200	452,600	126,000	1569.3
Tot	Tot	382,963,000	287,000,000	346,500,000	85,900,000	818	35,590,000	54,000,000	30,770,000	1,130,000	5959.0
		Shares									
BZ	Industries extractives	0.26	0.26	0.28	0.30	0.30	0.30	0.05	0.10	0.05	0.12
CA	Fabrication de denrées alimentaires, de boissons et de produits à base de tabac	0.25	0.27	0.27	0.21	0.18	0.21	0.27	0.20	0.20	0.01
CB	Fabrication de textiles, industries de l'habillement, industrie du cuir et de la chaussure	0.19	0.18	0.18	0.16	0.19	0.19	0.18	0.23	0.33	0.02
CC	Travail du bois, industries du papier et imprimerie	0.11	0.11	0.10	0.10	0.09	0.10	0.13	0.10	0.10	0.01
CD	Cokéfaction et raffinage	0.05	0.04	0.07	0.07	0.17	0.15	0.61	0.23	0.09	0.32
CE	Industrie chimique	0.40	0.43	0.28	0.25	0.29	0.30	0.26	0.22	0.15	0.08
CF	Industrie pharmaceutique	0.24	0.25	0.19	0.14	0.20	0.20	0.24	0.17	0.30	0.11
CG	Fabrication de produits en caoutchouc et en plastique ainsi que d'autres produits minéraux non métalliques	0.26	0.25	0.27	0.28	0.27	0.29	0.31	0.29	0.24	0.05
CH	Métallurgie et fabrication de produits métalliques à l'exception des machines et des équipements	0.17	0.16	0.18	0.19	0.18	0.19	0.18	0.18	0.27	0.03
CI	Fabrication de produits informatiques, électroniques et optiques	0.20	0.19	0.32	0.37	0.32	0.34	0.35	0.27	0.32	0.06
CJ	Fabrication d'équipements électriques	0.20	0.20	0.24	0.21	0.22	0.22	0.26	0.28	0.52	0.06
CK	Fabrication de machines et équipements n.c.a.	0.15	0.13	0.18	0.17	0.18	0.19	0.17	0.13	0.20	0.05
CL	Fabrication de matériels de transport	0.13	0.11	0.14	0.25	0.23	0.24	0.18	0.14	0.17	0.06
CM	Autres industries manufacturières ; réparation et installation de machines et d'équipements	0.15	0.16	0.14	0.13	0.13	0.13	0.14	0.14	0.09	0.01
DZ	Production et distribution d'électricité, de gaz, de vapeur et d'air conditionné	0.85	0.88	0.79	0.81	0.78	0.81	0.97	0.97	0.60	0.01
EZ	Production et distribution d'eau ; assainissement, gestion des déchets et dépollution	0.09	0.08	0.26	0.25	0.29	0.31	0.13	0.12	0.17	0.04
FZ	Construction	0.14	0.17	0.14	0.12	0.12	0.15	0.34	0.23	0.79	0.00
Tot	Tot	0.41	0.47	0.22	0.23	0.18	0.21	0.22	0.16	0.27	0.01

B Empirical Appendix

B.1 Variable Construction

B.1.1 Natural disaster proxy

In recent years, several studies have utilised data on natural disasters and extreme weather events from the Emergency Events Database (EM-DAT). In Table B1, we compare our baseline proxy with those used in four recent papers.

Some studies, such as Gu and Hale (2023), Feng and Li (2021), and Hale (2022), focus exclusively on climate change-related events (i.e., climatological, meteorological, and hydrological disasters). Others, such as Ferriani et al. (2023), also incorporate geophysical shocks (e.g., earthquakes, mass movements, and volcanic activities). For our analysis, we include only climate change-related hazards, as these are generally less predictable than geophysical events. The EM-DAT dataset includes only shocks that meet at least one of four criteria related to the number of deaths, the number of people affected, or the declaration of a state of emergency. Some studies, such as Hale (2022), select firms based on these criteria alone. In contrast, our study, like Gu and Hale (2023), applies additional conditions on the affected population and damage, as outlined by Monetary and Dept. (2020).

Finally, to the best of our knowledge, this is the first paper to conduct a global firm-level analysis using EM-DAT data aggregated at the subnational level.

Table B1: Proxies

	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

B.1.2 Ownership Networks

Business Groups (BGs) as a set of at least two legally autonomous firms that function as a single economic entity through a common source of hierarchical control via equity stakes (Altomonte et al., 2021). Rungi et al. (2017) introduced an innovative network framework to study the extent of a firm boundary when coordinated management decisions have to be transmitted along alternative and often overlapping ownership paths. Applying their algorithm to a dataset of 53.5 million companies operating in 206 countries, they analyse some specific properties that characterise pyramidal corporate structures. Altomonte et al. (2021) use the same empirical framework to test a new theory of business groups as knowledge-based hierarchies. They predict that institutional environments, production possibilities, communication costs and manager skill premium influence the rise of hierarchical business groups, with several layers of subsidiaries directly or indirectly controlled by the parent firm. In this study, we contribute to this literature, creating a longitudinal business group dataset over the period 2009-2021 and analysing the way exogenous shock propagate through the ownership network, affecting its internal structure.

B.1.2.1 Means of control

Parent firms exert control on their business group in four ways:

1. Direct control: the parent firm has the majority of voting rights in the subsidiary;

$$d_{ji} = \begin{cases} 1 \text{ if } \exists j : w_{ji} > 0.5 \\ 0 \text{ if } \exists k \neq j : w_{ki} > 0.5 \\ w_{ji} \text{ otherwise} \end{cases}$$

2. Indirect control by transitivity: when a subsidiary has the majority of voting rights

in another company

$$t_{ji} = \begin{cases} 1 \text{ if } \exists j, l : w_{jl} > 0.5 \text{ and } w_{li} > 0.5 \\ 0 \text{ if } \exists k \neq j : w_{kl} > 0.5 \text{ and } w_{li} > 0.5 \\ d_{ji} \text{ otherwise} \end{cases}$$

3. Indirect control by consolidation of voting rights: when a majority of voting rights is reached after summing up the stakes that are held by more than one subsidiary, or by the parent company and one or more subsidiaries.

$$c_{ji} = \begin{cases} 1 \text{ if } t_{ji} + \sum_{q:t_{jq}=1} t_{qi} > 0.5 \\ 0 \text{ if } \exists k \neq j : t_{ki} + \sum_{q:t_{kq}=1} t_{qi} > 0.5 \\ t_{ji} \text{ otherwise} \end{cases}$$

4. Dominant stake: when the shareholder does not have a majority control, but has a control probability (measured using the Banzhaf index) higher than 0.5.

$$b_{ji} = \begin{cases} 1 \text{ if } \pi_{ji} > 0.5 \\ 0 \text{ if } \exists k \neq j : \pi_{ki} > 0.5 \\ t_{ji} \text{ otherwise} \end{cases}$$

To illustrate the complexity characterising some of these corporate groups, Figure A2a presents the ownership network led by an anonymous European manufacturing firm, while Figure A2b shows the relative number of affiliates by ownership layer.

Although confidentiality constraints prevent us from disclosing the spatial distribution of the group, we successfully geocoded all parent and affiliate firms in our dataset and assigned them to subnational regions using the GADM classification, which divides the world into 3,600 regions.

The anonymous manufacturing firm has a majority of voting rights only for 50 affiliates, it indirectly controls a broad business group counting over 380 affiliates in 24 countries.

B.1.3 Automation proxy

Our measure of automation is based on detailed firm-level customs data on imports of machines from abroad. Instead of focusing only on industrial robots (defined by the 8-digit code 84795000), we follow Aghion et al. (2020) and identify a broader group of automation technologies belonging to two main categories: HS84 "Nuclear reactors, boilers, machinery and mechanical appliances; parts thereof" and 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 choose to exclude several detailed product categories related to information and communication technologies and transportation. Eventually, we retain only 420 categories out of 1,338 belonging to the two macro-groups.

This variable, that we classify as ' automation', provides a detailed identification of automation technologies, but it overlooks the domestic purchase of industrial robots. However, as reported by Bonfiglioli et al. (2020), robot imports as a proxy for automation is supported by the industry's high concentration, with Japan and Germany alone making up 50% of global exports and France contributing about 5%. Moreover, we exclude from our sample firms in the 'Installation and Repair of Machinery and Equipment' industry, which could include imports by robot integrators or resellers.

For each firm-year, we have information on price and quantity of the imported automation products. We exploit this information to calculate a firm-level automation stock using the perpetual inventory method. Following Graetz and Michaels (2018), we assume a depreciation rate of 10%. Furthermore, we classify as 'robot adopters' all firms from the first time they invest in these technologies for a value equal or grater than €2,500.

C Alternative specifications

C.1 Natural disasters and inward FDI flows

To provide further evidence on the macroeconomic effect of natural disasters, we estimate a country-level regression which investigates the relationship between the net FDI flows as a share of GDP (as recorded in $t-1$) and various types of natural disasters. The specification takes the following form:

$$FDI^{q}_{izt} = X'_{iz,t-1}\beta_1 + ND^{f}_{iz,t-1} + \alpha_i + \gamma_t + \lambda_{zt} + \varepsilon_{izt} \tag{C1}$$

where FDI^{q}_{izt} are inflow FDI to country i in year t, $X'_{iz,t-1}$ is a vector of time-varying country-level characteristics measured in $t-1$ and α_i, γ_t and λ_{zt} are respectively country i, year t and income group z[47] times year fixed effects. The variable $ND^{f}_{iz,t-1}$ is a simple dummy which equals one when a disaster of type f occurred in $t-1$ in country i.

Table C1: Target country-level analysis

Dep. Var.: ln(IFDI/GDP)	(1)	(2)	(3)	(4)	(5)	(6)
Any disaster	-0.0483*	-0.0468*	-0.0532*			
	(0.0286)	(0.0269)	(0.0301)			
Climatological				-0.0149**	-0.0193**	-0.0206**
				(0.00647)	(0.00770)	(0.00877)
Hydrological				-0.0494**	-0.0415**	-0.0452*
				(0.0248)	(0.0207)	(0.0231)
Meteorological				-0.0143	-0.0217	-0.0239
				(0.0175)	(0.0207)	(0.0227)
Observations	4,084	4,084	3,543	4,084	4,084	3,543
R^2	0.155	0.181	0.183	0.156	0.181	0.184
Macroeconomic covariates	-	-	✓	-	-	✓
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	-	-	✓	-	-
Income group × Year FE	-	✓	✓	-	✓	✓

Notes: This table reports the estimates of the model presented in Equation (C1). Robust standard errors are clustered at the country level and reported in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

[47] We use the standard UN classification that identifies advanced, emerging and low-income economy

This framework provides preliminary insights into how natural disasters affect countries' short-term ability to attract FDI. However, it does not account for changes in performance and industrial composition in the origin countries. Table C1 presents the estimates of the model in Equation (C1). Column (1) shows a negative effect of natural disasters on inward FDI flows, with an average decline of 4.8% in FDI flows in the year following the event. The coefficient is only significant to the 10% level, but remains substantially unaltered in column (2), when we include income group-year fixed effects and in column (3) when we add some relevant time-varying characteristics. Columns (4)-(6) separate the effects of climatological, hydrological, and meteorological disasters, with significant negative effects observed for the first two disaster types.

C.2 Subsidiary-level analysis

C.2.1 Disaster Intensity

Table C2 replicates our baseline subsidiary-level results, using an alternative proxy for natural disaster, namely the disaster intensity, computed as the dagame-to-GDP ratio. According to the estimates in column (1), natural disaster causing a damage of 10% of the national GDP increases the likelihood of divestment by 6%. The result is stable when we include the full set of fixed effects and increases to 10% after including bilateral and country-specific time varying controls.

Table C2: Disaster intensity

Dep. Var.: Divestment	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Natural Disaster	0.00603*	0.00965***	0.00511***	0.00566***	0.00520***	0.00526***	0.0100***
	(0.00331)	(0.00348)	(0.00181)	(0.00172)	(0.00154)	(0.00155)	(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-level controls	-	-	-	✓	✓	✓	
Country-level controls	-	-	-	-	✓	✓	
Bilateral controls	-	-	-	-	-	✓	
Subsidiary FE	✓	✓	✓	✓	✓	✓	✓
Parent country × year FE	✓	✓	-	-	-	-	-
Year × IncomeGroup × Region × Industry FE	-	✓	✓	✓	✓	✓	-
Parent firm × year FE	-	-	✓	✓	✓	✓	✓
Destination Country × Industry × Year FE	-	-	-	-	-	-	✓

Notes: This table presents regression results of the model presented in Equation (3). All specifications include subsidiary fixed effects. Columns (1)-(2) include parent country-year fixed effects. Columns (2)-(6) include income group-macroregion-industry-year fixed effects. This term is replaced in column (7) by destination country-industry-year fixed effects. Columns (3)-(7) include parent firm-year fixed effects. A complete list of subsidiary-level and control-level covariates is reported in Table A.2.2. Robust standard errors are clustered two-way by subsidiary firm and region and reported in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Overall, the results are broadly in line with the ones reported in Table 5.

C.2.2 Shock types

Table C3 replicates our baseline subsidiary-level results, separately identifying the effect of climatological (droughts and wildfires), meteorological (storms and extreme temperatures), and hydrological (floods, avalanches, landslides, and mudslides) disasters.

Table C3: Shock types

Dep. Var.: Divestment	(1)	(2)	(3)	(4)
Climatological Disaster	0.0596***			0.0571***
	(0.00799)			(0.00870)
Hydrological Disaster		0.0247***		0.0252***
		(0.00781)		(0.00814)
Meteorological Disaster			0.0229**	0.0239**
			(0.00997)	(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	✓	✓	✓	✓

Notes: This table presents regression results of the model presented in Equation (3). The estimates mimic the ones presented in column (7) of Table 5, but are specifically focused on climatological (droughts and wildfires), meteorological (storms and extreme temperatures), and hydrological (floods, avalanches, landslides, and mudslides) disasters. All specifications include subsidiary, destination country-industry-year and parent firm-year fixed effects. Robust standard errors are clustered two-way by subsidiary firm and region and reported in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

C.2.3 No previous exposure

Table C4 replicates our baseline subsidiary-level results, excluding all regions which recorded any type of natural disaster between 1990 and 2010.

Table C4: Subsidiary-level Analysis - No Previous Exposures

Dep. Var.: Divestment	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Natural disaster	0.0425***	0.0580***	0.0491***	0.0468***		0.0449***	0.0655*
	(0.00835)	(0.0120)	(0.00870)	(0.0087)		(0.00871)	(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

Notes: This table presents regression results of the model presented in Equation (3). All specifications include subsidiary, destination country-industry-year and parent firm-year fixed effects. The proxy for BG historic risk exposure is constructed as the pre-sample share of affiliates located in a territory hit by a natural disaster between 1990 and 2010. '1st layer' affiliates are firms directly controlled by the parent firm, '2nd layer' firms are controlled through a single intermediary, whereas '3rd+ layer' firms are located further away from the centre of the network. Columns (1)-(5) cover the whole sample, whereas columns (6) and (7) only include firm located, respectively, in high-income and low/medium income countries. Robust standard errors are clustered two-way by subsidiary firm and region and reported in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

C.3 Business group-level analysis

C.3.1 No previous exposure

Table C5 replicates our baseline business group-level results, using a measure of disaster exposure which disregard events that take place in regions which recorded a natural hazard between 1990 and 2010.

Table C5: Business group-level analysis - No previous exposure

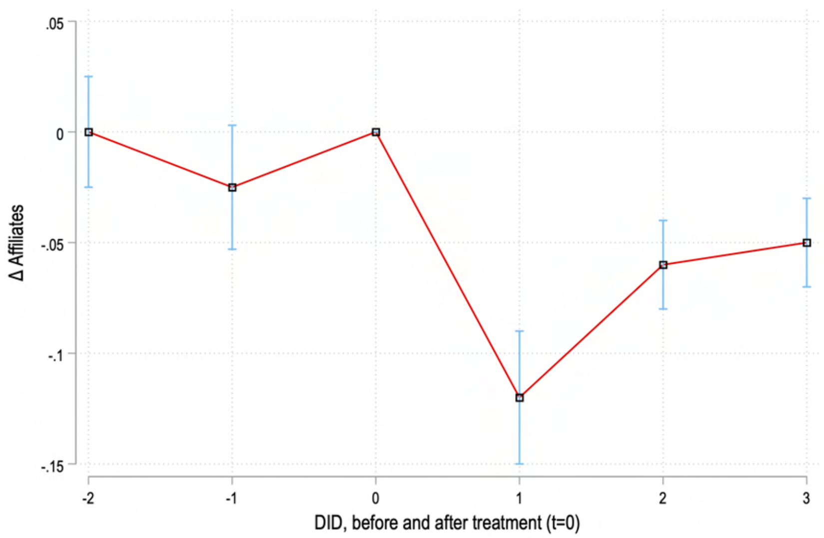
	(1)	(2)	(3)	(4)	(5)
Dep var.: Δ Affiliates					
Natural Disasters	-0.172***	-0.166***	-0.198***	-0.169***	-0.185**
	(0.0280)	(0.0264)	(0.0300)	(0.0439)	(0.072)
Observations	2,190,298	2,190,170	269,266	552,143	65,027
R-squared	0.158	0.162	0.175	0.197	0.140
BG FE	✓	✓	✓	✓	✓
Year FE	✓	-	-	-	-
Parent country$\times$Year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

Notes: This table presents regression results of the model presented in Equation (4). All specifications include parent country-year fixed effects. In column (2)-(5) the specification incudes home country-year fixed effects. Estimates presented in column (3) refer to business groups with at least 5 subsidiaries at the beginning of the period. Column (4) focus on business group whose parent firm is located in a safe country. Column (5) includes only business groups led by a France based firm. Robust standard errors are clustered at the parent firm-level and reported in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

C.3.2 Event Study

In Figure C1, we test for pre-trends, by implementing the robust DID estimators developed by De Chaisemartin and d'Haultfoeuille (2024).

Figure C1: Business Groups - Event Study



C.4 Narrow Offshoring

Feenstra and Hanson (2003) define 'narrow offshoring' as the procurement of inputs from the same industry as the producing firms. This concept is based on the assumption that the closer the inputs are to the final products, the more likely it is that the firm's labour could have produced those inputs internally. Following Hummels et al. (2014), we adapt this concept to individual firms, defining narrow offshoring as the total imports within the same 4-digit CPA2.1 category as the goods sold by the firm, whether domestically or as exports.

In Table C6 we exploit firm-level transactions recorded by the population of manufacturing firm in France to test the effect of natural disasters on both total imports and same-sector ('narrow offshoring') transactions. This approach suffers the limitations emerged in the previous literature, most notably the need to aggregate disasters at the country level (even for very large countries) and a focus limited to direct transactions, that overlooks the complex interactions that characterise modern global value chains. On the other hand, this specification complements the analysis conducted in Section 5.2, with some direct evidence about the backshoring of certain tasks.

Table C6: Bilateral trade-level Analysis

Dep var.	Imports share			
	(1)	(2)	(3)	(4)
Natural disaster	-0.0239***	-0.0236***	-0.0001	-0.0377***
	(0.006)	(0.007)	(0.0004)	(0.0078)
Observations	1047077	975295	276768	584330
R-squared	0.62	0.78	0.83	0.78
	Narrow offshoring			
	(5)	(6)	(7)	(8)
Natural disaster	-0.116*	-0.0948	-0.05	-0.185***
	(0.06)	(0.066)	(0.081)	(0.090)
Observations	561,021	549,530	276,768	343,983
R-squared	0.78	0.85	0.83	0.85
Countries	All	All	AE	EME/LIC
Firm×Origin country FE	✓	✓	✓	✓
Year FE	✓	-	-	-
Year×industry FE	-	✓	✓	✓

Notes: Robust standard errors are clustered at the subsidiary firm level and reported in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

In Panel A, we investigate the effect of natural disasters on imports of intermediate products. In the baseline TWFE specification, the idiosyncratic shock reduces imports of intermediates by over 2% standard deviations. The result is robust to the inclusion of industry times year fixed effects and appears to be driven by low- and medium-income countries. In Panel B, we focus on the impact on 'narrow offshoring'. Once again, the effect on transactions with high-income countries is not significant, whereas we find a small negative effect on transactions with low-income countries. Overall, the findings are in line with the results presented in Section 5.2.

C.5 Controlling for non-random shock exposure

In Table C7 and C8 we replicate the analyses reported respectively in Table 9 and 11, controlling for the non-random shock exposure. We do so by adopting the approach developed by Borusyak and Hull (2023) and presented in Section 5.3.1.

Table C7: Firm-level outcomes (controlling for non-random exposure)

	(1) Employment	(2) Employment	(3) Intermediates	(4) Intermediates	(5) Machinery	(6) Machinery
			All			
Disaster exposure	0.00224	0.00386	-0.0233*	-0.0294**	0.0472**	0.0548**
	(0.00256)	(0.00257)	(0.0135)	(0.0141)	(0.0234)	(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	0.00503**	-0.0011	-0.00435	0.0642**	0.0721**
	(0.00337)	(0.00347)	(0.0223)	(0.0215)	(0.0313)	(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	0.00233	-0.0524***	-0.0619***	0.0214	0.0262
	(0.00392)	(0.00378)	(0.0134)	(0.0139)	(0.0354)	(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 $\times$ Year FE	-	✓	-	✓	-	✓

Notes: This table presents regression results of the model presented in Equation (6). The measure of exposure to natural disasters is presented in Equation (5). All specifications include firm fixed effects. Specifications in columns (1), (3), (5), (7) include year fixed effects, whereas the ones presented in columns (2), (4), (6) and (8) include 4-digit industry-year fixed effects. Robust standard errors are two-way clustered at the firm- and business group-level and reported in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table C8: Worker-level Analysis (controlling for non-random exposure)

Dep var.	Hourly Wage					
	All manufacturing		Robot-intensive industries		Other industries	
	(1)	(2)	(3)	(4)	(5)	(6)
Natural disasters	0.0598**	0.0673**	0.0706**	0.0798**	0.0131	0.0171
	(0.0025)	(0.0262)	(0.0291)	(0.0307)	(0.0141)	(0.0145)
Routine cognitive		-0.0203***		-0.0188***		-0.0263***
		(0.00197)		(0.00243)		(0.00374)
Natural disasters x Routine cognitive		-0.0294***		-0.0343***		-0.0205*
		(0.0077)		(0.0097)		(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	✓	✓	✓	✓	✓	✓

Notes: This table presents regression results of the model presented in Equation (7). The measure of cognitive task intensity is constructed using O*NET data, as discussed in Section 3.5. Robust standard errors are two-way clustered at the worker and parent firm-level and reported in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.