How Shocks Travel: The Cross-Border Impact of Natural Disasters in Firm Networks

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Abstract

We study how disruptions in global production networks propagate across borders through firm-to-firm linkages. Using a novel dataset that combines U.S. Bill of Lading microdata, geocoded records of global natural disasters, Orbis ownership linkages, and firm-level financial data from Compustat, we study exogenous shocks to foreign input suppliers and trace their effects on U.S.-based firms. We implement an event-study strategy with staggered adoption of treatment and exploit the exogeneity of natural disasters to estimate their impact on firm outcomes. As a first stage, we show that natural disasters abroad are associated with a decline in the exports of affected foreign firms from which U.S. firms source their intermediate inputs. Building on this, we examine how these shocks propagate to U.S. firms connected through global value chains, and whether the strength of the transmission depends on the nature of the relationship, particularly in the presence of ownership ties. This approach allows us to quantify the role of intra-firm linkages in amplifying the cross-border effects of supply chain disruptions. Our [preliminary] findings suggest that U.S. firms experience declines in imports, following a shock to their foreign suppliers, with larger effects observed when the relationship involves common ownership. Furthermore, by studying the role of ownership, we find [suggestive] evidence that foreign affiliates located in unaffected districts also respond to shocks affecting related parties elsewhere, pointing to an internal reallocation of production within multinational networks.

Keywords: Multinational firms, production networks, shock propagation.
JEL Codes: F23, F14, L14, L23.

1 Introduction

Recent global trade disruptions, including the U.S. China trade war, the COVID 19 pandemic, and the Russia Ukraine conflict, have highlighted the vulnerabilities faced by firms operating within international production networks. While global value chains have delivered efficiency gains through international specialization, they have also increased firms' exposure to external shocks that can severely disrupt production. In particular, the reliance on foreign input suppliers, within and outside the boundaries of the firms can lead to a disruption of production when source countries experience negative shocks.

Two opposite forces are in play. On the one hand, increases in production sharing across global value chains and the corresponding decline in the value-added share of a given country's exports can make the impact of trade disruptions, and tariff and non-tariff shocks more severe. On the other hand, given the prominence of multinational firms in global production, it may be easier than ever to relocate production across country borders, partially offsetting the effects of idiosyncratic shocks on production and prices (Flaaen et al., 2021).

Despite its policy relevance, academic research on the effects of trade shocks in the presence of cross-border ownership and intra-firm trade linkages remains limited, largely due to the lack of comprehensive data on cross-border activities of multinational firms. This paper examines how disruptions in global production networks propagate across borders through firm-to-firm linkages. The literature suggests that multinationals—defined as networks of production units under common ownership—may respond differently to economic shocks due to investment-specific relationships and financial interdependencies. Yet, whether cross-border trade disruptions affect firm performance differently depending on ownership ties between trading partners remains an open empirical question.

To address this question, we construct a novel dataset that combines (i) comprehensive information from the U.S. international trade transactions registered in the Bill of Lading (BoL), (ii) global data on extreme natural disasters as a source of identification, (iii) information on ownership linkages within and across borders provided by Orbis, (iv) and firm-level financial data from Compustat.

We implement an event study strategy with staggered adoption of treatment and exploit the exogeneity of natural disasters to estimate their impact on firm performance. First, we estimate the direct effect of the incidence of natural disasters on foreign firms that experience the shock and the indirect effect on U.S. importers that source intermediate inputs from those affected suppliers, regardless of common ownership. We then examine whether the strength of the transmission depends on the nature of the relationship, particularly in the presence of ownership ties. To better understand the role of common ownership in the propagation of shocks, we contrast the impact of disruptions on intra-firm trade versus arm's-length transactions. Furthermore, since we observe the network of multinationals' affiliates across countries—including those in locations not affected by shocks—we can measure the extent to which new trade relationships were formed with related parties in unaffected countries, or whether there was a significant increase in imports from those foreign affiliates.

As a first stage, we show that natural disasters abroad are associated with a decline in the exports of foreign firms that are directly affected by the shock and from which U.S. importers source intermediate inputs. We find that following the first shock, these firms experience a 25 percent reduction in export value relative to the average export value of the control group[2]. This result supports the identifying assumption that the shock significantly impacts supplier performance and motivates the analysis of downstream effects on U.S. firms. It also provides the basis for examining how such disruptions propagate through global value chains. We then examine whether these shocks translate into declines in the performance of U.S. firms connected through global value chains, and whether the strength of the transmission depends on the nature of the relationship—particularly in the presence of ownership ties. We find [suggestive] evidence that U.S. importers indirectly exposed to affected suppliers experience a reduction in overall import growth, with [preliminary] evidence pointing to larger effects among firms with intra-firm linkages. Additionally, a separate analysis using the Orbis dataset suggests that multinational affiliates in unaffected regions respond to shocks affecting related parties elsewhere in the network, consistent with internal reallocation of production.

We contribute to two literature branches. First, we contribute to the literature on the role of weather shocks for propagation through production networks (Khanna et al., 2022; Freund et al., 2022; Lee and Han, 2022; Längle et al., 2021; Carvalho et al., 2021; Boehm et al., 2019; Barrot and Sauvagnat, 2016), firm relocation (Castro-Vincenzi, 2022; Balboni et al., 2023), and others (Blaum et al., 2023; Fort et al., 2023; Ayyagari et al., 2022). Most of this existing work on the transmission of weather shocks focuses on domestic production networks and is agnostic to ownership linkages and their type of customer-supplier relationship. Notable exceptions are Boehm et al. (2019) and Freund et al. (2022) who focus on the supply-chain effects of Japanese earthquake of 2011 on the US affiliates of Japanese multinationals. We leverage weather shocks that propagate across international production networks and account for the role of multinationals in the transmission of these shocks.

[2]Export value is calculated by multiplying shipment quantities from the Bill of Lading data with unit values from U.S. Census trade statistics (at the HS6-country-year level). Effects are expressed relative to the average export value of firms in the control group with positive exports in our window of study (2007-2018)

Second, we contribute to the literature of multinationals (Li, 2021; Antràs, 2022; Arkolakis et al., 2018; Cravino and Levchenko, 2017; Atalay et al., 2014; Conconi et al., 2022; Yeaple, 2009). Focusing on ownership linkages, Cravino and Levchenko (2017) study how multinational firms contribute to the transmission of shocks across countries. Relative to this paper, we focus on the effects of intra-firm transactions across the worldwide network of affiliates of US multinationals and on whether the effects are different when trade is carried with unrelated parties.

The rest of the paper is organized as follows. Section 2 describes our data sources and how we process the data. In sections 3 we present summary statistics. Sections 4 and 5 outlines our empirical strategy and present our results. Section 6 concludes.

2 Data

To understand how the nature of production networks affects the propagation of shocks across countries, we assemble a novel dataset that combines four micro-level sources: (1) the universe of U.S. maritime import transactions for the period 2007–2018, extracted from the U.S. Bill of Lading; (2) detailed information on the type, exact location, and number of people affected by major natural disasters worldwide during the sample period, sourced from the EM-DAT and SHELDUS databases; (3) ownership linkages between firms within and across countries, obtained from Orbis; and (4) financial data on non-financial firms from Compustat. The combined dataset provides a more complete picture of the global operations and international trade transactions of U.S. companies, including U.S. multinationals and affiliates of foreign multinationals operating in the United States.

First, we start with U.S. maritime import transactions from the Bill of Lading data for the period 2007–2018. This dataset allows us to identify importing firms, their foreign suppliers, and the scope of their international transactions—including the number of transactions, the duration of relationships, and the types and quantities of goods traded. Using complementary trade data from the U.S. Census, we construct unit prices at the HS6–country pair level. We then use these unit prices in combination with the quantities in the Bill of Lading data to construct a proxy for the value of imports at the firm level.

Second, we bring in global data on the location, duration, and severity of natural disasters from the Emergency Events Database (EM-DAT) and the Spatial Hazard Events and Losses Database for the United States (SHELDUS), covering the period 2007–2020. Using geocoded firm locations derived from physical addresses, we construct a time-varying dummy variable that indicates whether a natural disaster occurred in the same district as the firm in a given period. This allows us to identify disaster exposure for foreign firms—with which U.S. firms maintain trade or ownership linkages—based on the timing and location of shocks.

Third, we merge our data with ownership linkages from the Orbis database, which is designed for corporate users seeking detailed information on the ownership structures, hierarchies, and contact details of private and public firms worldwide. Orbis provides granular data on firm-to-firm ownership relationships across countries, allowing us to identify (1) which firms are headquartered in the U.S. and which are affiliates of foreign-headquartered companies, and (2) whether a given firm is part of a multinational corporation, including the countries and sectors in which the corporation operates. For each multinational group, Orbis includes information on affiliate names, countries of operation, and financial indicators such as sales and assets. This allows us to distinguish whether a foreign supplier is part of the same multinational group as the U.S. firm (intra-firm relationship) or is an independent trade partner (arm's-length relationship). Importantly, Orbis also enables us to identify foreign affiliates that belong to the same corporate group but do not engage in direct trade with the U.S. firm.

Finally, we link this combined dataset to financial data for non-financial firms from the Compustat North America Fundamentals Quarterly database for the period 2007–2020. This includes firm-level measures of sales, cost of goods sold, and profits, as well as stock price data from the Center for Research in Security Prices (CRSP) and Compustat Global.

While none of these data sources are novel on their own, our contribution lies in merging them into a unified framework. This is a nontrivial task that requires, in particular, geocoding the locations of millions of firms and thousands of natural disaster events to precisely identify which firms are directly affected by specific disasters. To our knowledge, this is the first time these four datasets have been integrated. The following sections provide a detailed description of each dataset.

2.1 Firm-to-firm trade transactions from Bill of Lading records

Information on international trade transactions are from the U.S. shipment-level bill of lading (BoL) compiled and provided by S&P Panjiva[3]. The original dataset contains over 155

[3] A bill of lading in shipping is a record of the traded goods which have been received on board. It is a legal document that establishes an agreement between a shipper and a transportation company for the transportation of goods. Transportation Company (carrier) issues these records to the shipper. A bill of lading indicates a particular carrier through which the goods have been placed to their final destination and the conditions for transporting the shipment to its final destination. A BoL contains detail information such as both the shipper and consignee name and address, description of the goods, vessel name, transport company name, ports of loading and unloading, weight, and quantity. Panjiva acquires these data by

million transaction-level records of goods traded across borders since 2007, including information on the date of the transaction, port of landing, name and address of the exporter (shipper) and the importer (consignee), the product description, and the quantity transacted.

Panjiva enhances the dataset by (1) assigning a Harmonized System (HS) product code to each product description included in the BoL; (2) providing a unique identifier to each importer (consignee Panjiva ID) and exporter (shipper Panjiva ID), allowing the longitudinal tracking of firms engaged in international trade; and (3) including a unique company identifier variable[4]. These IDs are also available in the Compustat dataset, allowing us to match later on the Panjiva trade data with Compustat, a procedure we describe in detail below[5].

On top of this, we construct a measure of export value which, for each firm and period, captures the total value of goods exported to the United States. To do so, we merge the BoL data with official U.S. Census trade statistics, which report values and quantities at the HS10-country-year level. Since Panjiva provides product codes at the HS6 level, we compute weighted average unit values at the HS6-country-year level using the Census data. We then multiply these unit values by the quantity of each shipment recorded in the BoL to approximate the export value of each transaction. Aggregating across all shipments by firm and period, we obtain a proxy for the export value at the firm level. This measure allows us to track changes in export performance over time and to estimate the direct impact of natural disasters on affected foreign suppliers.[6]

collecting bills of lading from U.S. Customs and Border Protection (CBP).

[4]Panjiva links the BoL data to Capital IQ, another S&P Global dataset containing key company financial information, such as sales, costs of goods sold, and profits. This crosswalk between Panjiva and Capital IQ is particularly useful for us since Capital IQ contains two key identifiers—the Committee on Uniform Securities Identification Procedures number (CUSIP), used to identify U.S. and Canadian registered stocks, and the Central Index Key (CIK), assigned by the Securities and Exchange Commission.

[5]First, the provided HS product code is at six digits (around 6,000 products), rather than at 10 digits (more than 10,000 products) as recorded by the U.S. Census Bureau Customs data. Second, a given transaction can list multiple HS6 codes, but only one shipment weight in kilograms, making it impossible to distinguish the weight associated with each HS6. Third, Panjiva uses a text processing algorithm to map a given company name and address to a unique numerical ID. However, there is a fraction of cases in which the algorithm fails to recognize that two companies are the same legal entity, wrongly assigning different Panjiva ID numbers. We overcome this challenge by refining the procedure to assign a temporally consistent ID number to a company that appears in the data with slightly different spellings in names and/or addresses. Spelling differences in addresses are resolved by geocoding all addresses in the BoL dataset. For additional details about the BoL data for the U.S., see Flaaen et al. (2021) and Alviarez and Blyde (2021).

[6]To ensure consistency in the construction of export values, we drop observations where a single transaction lists multiple HS6 codes but only one quantity or weight, which makes it impossible to accurately allocate shipment value across products.

2.1.1 Geocoding firm addresses

In order to measure the distance between the physical address of the firm and the geographical location of any natural disaster, we proceed to convert the physical address component of all U.S. importers and their corresponding foreign partners into geographical coordinates (latitude and longitude). After harmonizing the address of those firms with the same Panjiva ID but with multiple spelling addresses, we provide longitude and latitude coordinates for 470,435 unique physical address of US importers and 995,568 unique physical address of foreign exporters[7].

To perform the geocode for each firm we use the most complete address available in the Panjiva BoL. Our preferred firm address is the one constructed by concatenating the individual components of a firm's physical address including route, city, region/state, postal code, and country. When the only non-empty individual components of the firm address where region/state and country, or country only, we use the firm's complete or full address in the BoL. The reason why we prefer the firm address constructed from parsed components is because it is more structured and therefore easier to geocode using API web services. Full address originally imputed in the BoL can be harder to parse as they are lacking punctuation separating the sub-components of the firm's address difficulting the geocoding process [8].

Table 1 shows that for 59 percent of the US importers the geocode was based on concatenated fields where all address components were available (route, city, region, postal code and country); whereas for 4.6 percent of them all components but route where available and used in the geocode of the physical address of the firm. For 25.5 percent the full address directed provided by BoL was used for geocode. For foreign exporters, we have to rely on the full address for 60 percent of firms.

[7]Our data has a total of 2,586,903 unique physical address for US importers and 2,782,417 unique physical address for foreign exporters. But, we prioritize the geocoding of the US firms, and their corresponding foreign exporters, that satisfy the following criteria: (1) US importers that are also exporters; (2) US importers in Panjiva that are also in the Compustat dataset; and (3) US importer has more than one foreign partner. After applying these restrictions we geocode 470,435 US address and 995,568 foreign address.

[8]The full address constructed by concatenating the individual address fields is often of better quality because of more systematic, and less subject to errors.

Table 1: Distribution of geocoded firms by address type (%)

	US Importers	Foreign Partners	Total
Full address	25.5	37.3	33.5
Route/City/Region/Postal Code/Country	59	21.1	33.3
City/Region/Postal Code/Country	4.6	7.7	6.7
City/Region/Country	3.5	11.7	9.1
Route/City/Region/Country	2.7	6.6	5.3
Route/Region/Postal Code/country	1.8	3.2	2.8
Other	2.9	12.4	9.3

Notes: This table shows the information contained in the firm's physical address used in the geocode process, for the US importers and the foreign exporters. The first row shows the percentage of addresses that were geocoded using the full or complete address directly reported by the Panjiva BoL. The next five rows show the percentage of geocoded addresses that were constructed by concatenating the individual components of the firm's physical address including route, city, region/state, postal code, and country. The last row shows the percentage of firms that use a different combination of route, city, region/state, postal code, and country, not listed in the previous rows.

We use the Geopy python library, which is a python client for several popular geocoding web services, such as Google maps, OpenStreet, among others. In particular, we use Bing Maps Location API geocoder to get the latitude and longitude corresponding to each address. Importantly, Bing API provides some variables that can be used to assess the quality of the outcome it generates. These variables are (1) confidence, (2) match codes, (3) inland, and (4) country. A given geocode has a medium or low confidence when only a subset of the address components are matched (i.e. if only the postal code of the full address is matched). The match code can take three values: good, ambiguous, and up-hierarchy, depending on whether the location has one or multiple returned matches. To further assess the reliability of the geocoding outcome, we create an inland variable that takes a value of one when according to the International Space Station the returned coordinates lay inland, and zero if they lay on the ocean. Second, since it is possible to retrieve the geographic variables associated with the coordinates provided by the Bing geocoding algorithm, we generate a dummy variable that compares the firm country with the country returned by Bing. Table 6 in Appendix A we show the quality assesment of our geocoding algorithm.

After obtaining the latitude and longitude of each firm, we use shapefiles from the Food and Agriculture Organization of the United Nations' Global Administrative Unit Layers (FAO GAUL) to assign an administrative unit (ADM) to each firm.[9] The shapefiles include three

[9] To obtain the shapefiles, we contacted `GeoNetwork@fao.org`. We thank Nelson Rosas Ribeiro Filho for

administrative levels: national, province, and district.

2.2 Natural disasters

To identify firm-level idiosyncratic shocks, we consider major natural disasters occurring around the word during the sample period 2007-2020. This information is retrieved from two main datasets.

1. EM-DAT (Emergency Events Database): For disasters taking place outside the U.S. we use the Emergency Events Database (EM-DAT) compiled by the Centre for Research on the Epidemiology of Disasters (CRED), which contains essential core data on the occurrence and the effects of over 22,000 mass disasters around the world. Critical for our research, EM-DAT lists all locations and number of people affected by the disaster and the time period in which it took place. The locations are identified by ADMs and then we aggregate the data at the ADM/time level, where time are weeks, months, quarters, or years.

2. SHELDUS (Spatial Hazard Events and Losses Database for the United States): For each natural disaster occurring in the U.S., the SHELDUS database provides information on the start date, the end date, and the Federal Information Processing Standards (FIPS) code of all affected counties. Through GIS, a ADM code–our geographic unit of analysis– is assigned to each FIPS code. We then aggregate the natural disasters data at the ADM/time level, where time is measure in weeks, months, quarters, or years.

We restrict the sample to major natural disasters. Specifically, we only consider those disasters-ADM pairs above the 90th percentile of the distribution of (1) the number of deaths, for disasters occurring outside the U.S., and (2) of the damage to property (measured in constant US dollars), for disasters occurring in the U.S.. We construct a dummy indicating whether a firm is located in the same administrative level as the major natural disaster[10]. We use the district-level matching to identify whether a firm in the Panjiva dataset was exposed to a natural disaster.

sharing the maps with us. The shapefiles required some adjustments, for which we computed the centroid of each polygon.

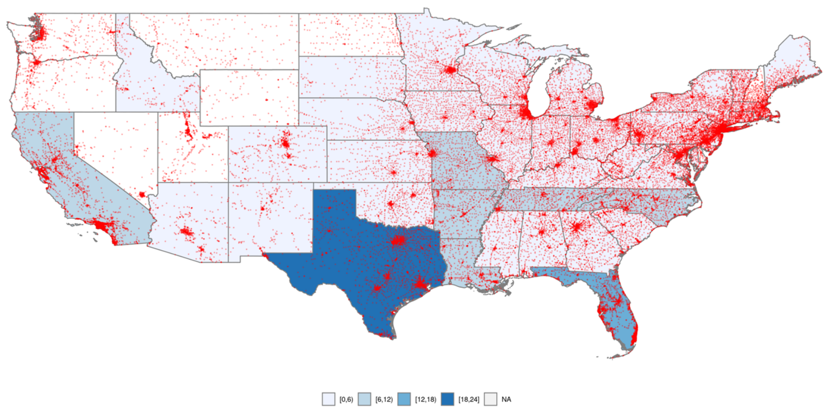
[10]The exact procedure we use to measure the impact of disasters on firms is as follows. First, we upload GAUL-FAO shape-files at administrative levels 1 and 2 and the geocoded information of all firms in our sample into QGIS (Quantum Geographic Information System), a software that supports the analysis of geospatial data. In QGIS, we assign a province (admin level 1) or a district (admin level2) to each firm, according to the administrative boundary within which the company is located. Additionally, QGIS provides the geographic coordinates (longitude and latitude) of the centroid of each administrative entity. Similarly,

Figure 1 shows the geographical distribution of the number of natural disasters in the U.S. (1a) and in the rest of the word (1b) and the geolocated firms used in our sample. Similarly, Figure 2 and Figure 3 show the spatial distribution of the number of two types of natural disasters, floods and storms respectively, for the U.S. and for the rest of the world.

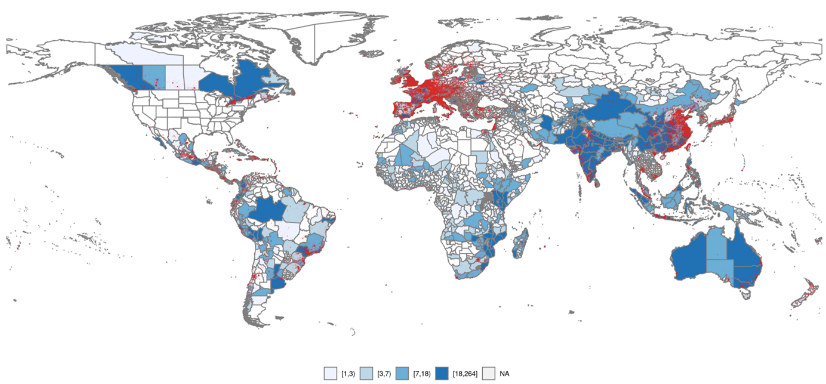
our data on natural disasters (EM-DAT and SHELDUS) contains detailed information on the location affected by each natural disaster at the admin level 1 mostly, or admin level 2 whenever available. Then we proceeded to construct measures of the impact of disasters on firms: First, we construct a dummy indicating whether a firm falls in the same administrative level as the natural disaster.

Figure 1: Spatial distribution of the number of natural disasters

(a) US



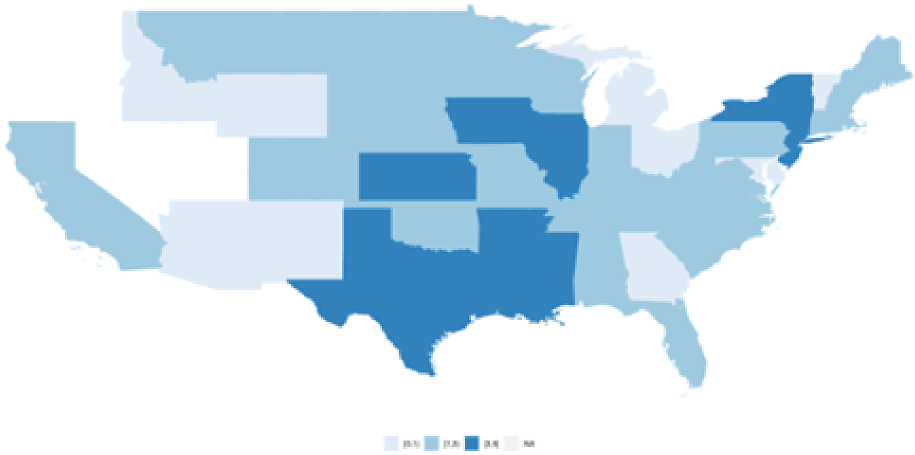
(b) Rest of the world



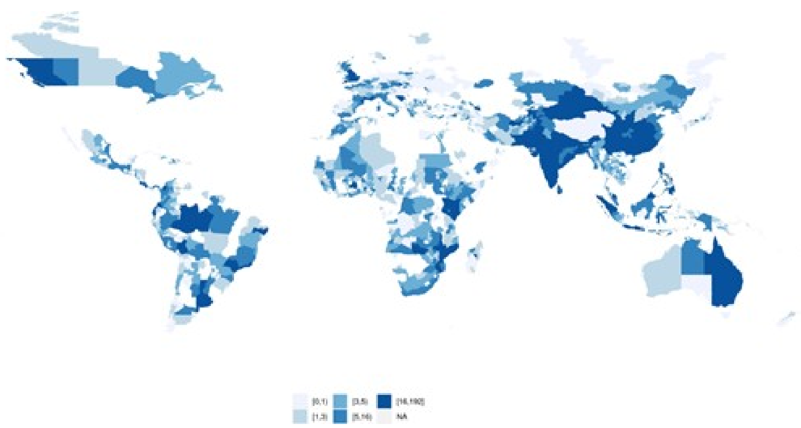
Notes: This figure shows the geographical distribution of the number of all natural disasters in the US occurring during the period 2000-2019 (top panel), and in the rest of the world for the period 2000-2020 (bottom panel). Maps are from the FAO GAUL and use first-level administrative units. Information of natural disasters in the US come from SHELDUS, and fro, EM-DAT for the rest of the world. Each red dot is the geolocation of a firm.

Figure 2: Spatial distribution of the number of floods

(a) US



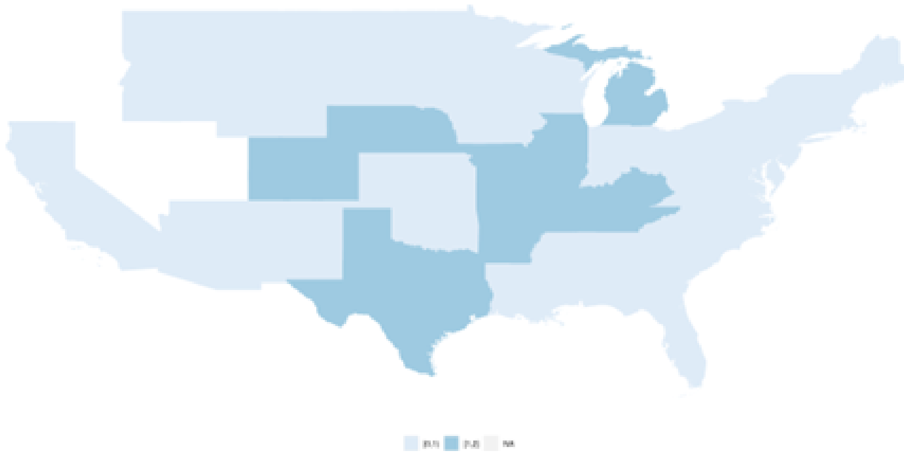
(b) Rest of the world



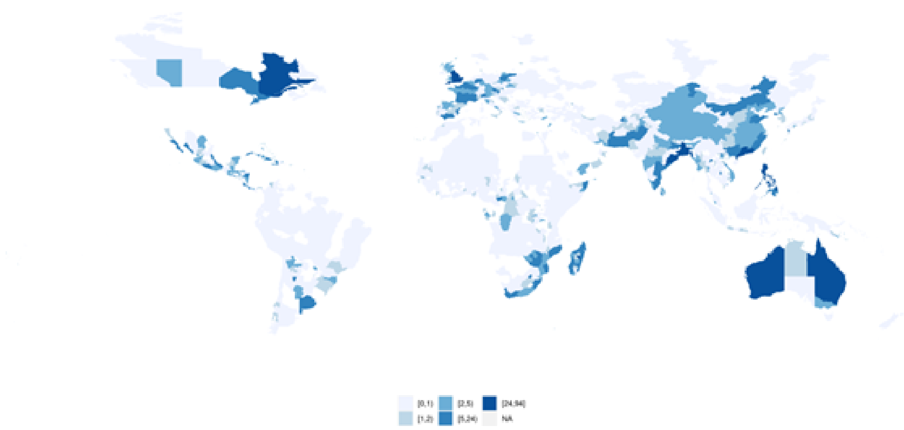
Notes: This figure shows the geographical distribution of the number of floods in the US occurring during the period 2000-2019 (top panel), and in the rest of the world for the period 2000-2020 (bottom panel). Maps are from the FAO GAUL and use first-level administrative units. Information of natural disasters in the US come from SHELDUS, and fro, EM-DAT for the rest of the world.

Figure 3: Spatial distribution of the number of storms

(a) US



(b) Rest of the world



Notes: This figure shows the geographical distribution of the number of storms in the US occurring during the period 2000-2019 (top panel), and in the rest of the world for the period 2000-2020 (bottom panel). Maps are from the FAO GAUL and use first-level administrative units. Information of natural disasters in the US come from SHELDUS, and fro, EM-DAT for the rest of the world.

Table 2 shows, for different types of natural disasters, the mean, standard deviation and key percentiles of the distribution of damage (measured in millions of constant US dollars) per affected county. Hurricanes, tornadoes, and floods are the most common natural disasters resulting in severe damage in the US. Table 3 presents a similar breakdown for the rest of the world, with the severity of disasters measured by total deaths in the affected country. Worldwide, earthquakes and storms are among the more deadly natural disasters.

Table 2: Natural Disasters in the US by type (damage to property)

	Mean	SD	p25	p50	p90	p95	p99	Max	Count
Flooding	144.6	647.6	8.6	18.5	166.4	582.8	2,218.0	8,688.9	20
Hail	771.6	1,001.2	98.6	288.8	2,300.0	3,215.1	3,215.1	3,215.1	5
Hurricane/Tropical Storm	376.6	1,563.9	9.6	29.8	700.0	1,165.4	7,643.7	20,000.0	26
Severe Storm/Thunderstorm	39.1	64.4	7.3	8.1	182.7	208.1	208.1	208.1	4
Tornado	90.1	299.7	8.2	16.3	160.6	300.0	1,679.3	3,104.9	24
Wildfire	392.4	1,595.3	7.7	27.8	674.7	1,484.7	11,257.8	11,257.8	9
Wind	60.4	201.0	10.0	10.0	30.0	348.9	1,217.5	1,217.5	4
Winter Weather	22.2	25.7	5.6	9.4	70.0	70.0	70.0	70.0	2
Total	282.6	1,277.7	9.4	23.1	500.0	981.1	5,976.1	20,000.0	94

Notes: The table shows, for different types of natural disasters in the US, the mean, standard deviation and the 25th, 50th, 90th, 95th and 99th percentiles of damage to property per affected county in adjusted million U.S. dollars, base year 2017, between 2000 and 2019. The last two columns report the maximum damage per county and the total number of natural disasters in the US for each type.

Table 3: Natural Disasters worldwide by type (total deaths)

	Mean	SD	p25	p50	p90	p95	p99	Max	Count
Flooding	144.6	647.6	8.6	18.5	166.4	582.8	2,218.0	8,688.9	20
Hail	771.6	1,001.2	98.6	288.8	2,300.0	3,215.1	3,215.1	3,215.1	5
Hurricane/Tropical Storm	376.6	1,563.9	9.6	29.8	700.0	1,165.4	7,643.7	20,000.0	26
Severe Storm/Thunderstorm	39.1	64.4	7.3	8.1	182.7	208.1	208.1	208.1	4
Tornado	90.1	299.7	8.2	16.3	160.6	300.0	1,679.3	3,104.9	24
Wildfire	392.4	1,595.3	7.7	27.8	674.7	1,484.7	11,257.8	11,257.8	9
Wind	60.4	201.0	10.0	10.0	30.0	348.9	1,217.5	1,217.5	4
Winter Weather	22.2	25.7	5.6	9.4	70.0	70.0	70.0	70.0	2
Total	282.6	1,277.7	9.4	23.1	500.0	981.1	5,976.1	20,000.0	94

Notes: The table shows, for different types of natural disasters, the mean, standard deviation and the 25th, 50th, 90th, 95th and 99th percentiles of the number of deaths of natural disaster worldwide. The last two columns report the maximum number of deaths and the total number of natural disasters worldwide for each type.

2.3 Global ownership linkages

Our data on firm-to-firm ownership linkages come from ORBIS, a worldwide dataset maintained by Bureau van Dijk that provides detailed information on ownership linkages between firms and across countries, contact information of private and public enterprises throughout the world, as well as information on firms' revenues and assets. ORBIS includes information on both listed and unlisted firms collected from various country specific sources, such as national registries and annual reports.

The main advantage of ORBIS is the scope and accuracy of its ownership information: it details the full lists of direct and indirect subsidiaries and shareholders of each company in the dataset, along with a company's global ultimate owner and other companies in the same corporate family. This information allows us to build links between affiliates of the same MNC, including cases in which the affiliates and the parent are in different countries. We specify that a parent should own at least 50 percent of an affiliate to identify an ownership link between the two firms. Thus, ORBIS allows us to identify the U.S. firms that are part of a larger multinational operation, distinguishing whether they are majority-owned U.S. affiliates of a foreign multinational, or U.S. parents firms that have majority-owned operations overseas. This gives us a more complete characterization of the operation of the MNCs located in the U.S. and their worldwide network of affiliates.

Most importantly for our analysis, ORBIS provides information on both, firms' names and physical addresses, making it possible to merge it with the BoL dataset, allowing us to identify which foreign exporters listed in the US import BoL belong to the same corporate group as the US importer and which ones are independent parties.

2.4 Financial firm-level information

In addition to analyzing the evolution of imports and exports, in ongoing work, we will assess how shocks to foreign partners propagate to U.S. firms by leveraging financial data from the Compustat North America Fundamentals Quarterly database. This module, part of the CRSP/Compustat Merged dataset, provides detailed balance sheet and performance variables for U.S. firms. Specifically, we retrieve information on sales, cost of goods sold, total assets, long-term debt, earnings per share, and dividends per share. We also retrieve return on assets (ROA), return on equity (ROE), and their standard deviations; as well as the ratios of non-interest income to operating income, loans to total assets, deposits to total assets, and equity to total assets. Finally, we include firm investment, measured as the ratio of quarterly capital expenditures to lagged quarterly property, plant, and equipment; and long-term leverage, defined as the ratio of total long-term debt to total assets.[11]

A key variable to analyze the propagation effects of idiosyncratic shocks is the firm's weekly

[11] These variables from the CRSP/Compustat Merged dataset have been widely used in academic research, including Bhargava (2014), Li (2021), and Almeida et al. (2009), among others.

stock return, for which we construct three alternative measures.[12] Returns are calculated following Compustat Global's documentation. Let P_t denote the firm's closing price on day t, A_t the adjustment factor for splits and dividends, and R_t the total return factor. Then, when all data are available, weekly returns are computed as:

$$\text{Return}_t = \left(\frac{P_t^{\text{adj}} \cdot R_t - P_{t-1}^{\text{adj}} \cdot R_{t-1}}{P_{t-1}^{\text{adj}} \cdot R_{t-1}} \right) \times 100 \tag{1}$$

where $P_t^{\text{adj}} = P_t / A_t$.

If the total return factor R_t is missing, returns are computed as:

$$\text{Return}_t = \left(\frac{P_t^{\text{adj}} - P_{t-1}^{\text{adj}}}{P_{t-1}^{\text{adj}}} \right) \times 100 \tag{2}$$

If instead the adjustment factor A_t is missing or zero, but R_t is available, returns are:

$$\text{Return}_t = \left(\frac{P_t \cdot R_t - P_{t-1} \cdot R_{t-1}}{P_{t-1} \cdot R_{t-1}} \right) \times 100 \tag{3}$$

Finally, if both A_t and R_t are missing, returns are calculated in the most basic form:

$$\text{Return}_t = \left(\frac{P_t - P_{t-1}}{P_{t-1}} \right) \times 100 \tag{4}$$

3 Summary Statistics

In this section, we present key summary statistics from our combined dataset. Tables 4 and 5 are based on the linked U.S. Bill of Lading and global natural disaster data. Table 4 focuses on U.S. importers among publicly listed firms (from Compustat), totaling over 220,000 importer-year observations. On average, 1.6% of these firms are directly affected by a major natural disaster in the U.S. in any given year. However, the probability that one of their foreign suppliers is hit by a natural disaster is notably higher, at 6.6%. The number of foreign suppliers per U.S. buyer is highly skewed, as is typical in firm-to-firm transaction

[12] In "Week1", weeks begin on the first available trading day of the year, repeating every 7 days. This definition does not guarantee 52 calendar weeks. "Week2" defines weeks from Monday to Friday, ending on the first Friday of each week. "Week3"—our preferred definition—calculates returns from Friday to the previous Friday, using the nearest trading day when needed. This method is more aligned with calendar weeks and captures events over weekends. It also simplifies compounding to lower frequencies such as monthly.

data: while the median buyer sources from only one foreign firm in a year, a small number of buyers engage with many suppliers.

Table 5 reports analogous statistics from the perspective of foreign sellers with at least one U.S. public firm as a buyer. We observe over 500,000 seller-year observations. The median foreign firm exports to only one U.S. importer, yet there is again substantial skewness in the distribution of U.S. customers. On average, 14.3% of foreign sellers experience a natural disaster in their own country, while 6.9% have a U.S. customer affected by a major domestic disaster.

These statistics highlight that being hit by a major natural disaster—either directly or indirectly through trade relationships—is rare but far from negligible. There is also meaningful heterogeneity in firms' exposure to shocks, supporting the use of natural disasters as a source of variation to study the propagation of idiosyncratic shocks through global value chains.

Table 4: Summary Statistics for U.S. Importers (Compustat Firms)

Variable	**Mean**	**St. Dev.**	**p1**	**p50**	**p99**
Disaster hits buyer$_t$	0.016	0.128	0.000	0.000	1.000
Disaster hits supplier$_t$	0.066	0.249	0.000	0.000	1.000
Number of suppliers$_t$	2.569	4.327	1.000	1.000	20.000

222,345 importer-year observations.

Notes: In this table we present descriptive statistics about US buyers from foreign partners. The sample is comprised by US buyers that purchased from foreign partners abroad and for which we also matched with Compustat. The first row indicates whether the US buyer was hit by a natural disaster. The second row indicates whether some supplier of a US buyer was hit by a natural disaster. The third row denotes the number of suppliers for a given US buyer.

Table 5: Summary Statistics for Foreign Sellers

Variable	**Mean**	**St. Dev.**	**p1**	**p50**	**p99**
Disaster hits seller$_t$	0.143	0.350	0.000	0.000	1.000
Disaster hits buyer$_t$	0.069	0.253	0.000	0.000	1.000
Number of buyers$_t$	1.504	1.713	1.000	1.000	20.000

550,974 seller-year observations.

Notes: In this table we present descriptive statistics about foreign sellers to US firms. The sample is comprised by foreign sellers that sold to US firms and for which we were able to matches US buyers to Compustat. The first row indicates whether the foreign seller was hit by a natural disaster. The second row indicates whether US buyer of a foreign seller was hit by a natural disaster. The third row denotes the number of buyers for a given foreign seller.

4 Empirical Strategy

To examine how natural disasters affect firm-to-firm trade, we implement an event-study framework with staggered treatment timing. Our empirical strategy relies on the exogeneity of natural disasters—sudden, location-specific events that are plausibly unrelated to firms' prior export performance. This setting allows us to estimate causal effects under the assumption that, absent the shock, treated and untreated firms would have followed similar trends. We focus on each firm's first exposure to a disaster in its region and estimate dynamic effects relative to the pre-treatment quarter. The specification includes firm and time fixed effects to absorb unobserved heterogeneity and common shocks, enabling us to capture both immediate and longer-run impacts. As a robustness check, we implement alternative estimators developed for staggered adoption designs, including those proposed by Borusyak et al. (2024), Sun and Abraham (2021), and Callaway and Sant'Anna (2021).

4.1 Estimating the Direct Effect on Exporting Firms

We begin by estimating how exports change after a supplier experiences a natural disaster in its country of operation. Our identification strategy leverages the exogeneity of natural disasters as idiosyncratic shocks to firm performance. We use quarterly firm-level export data from U.S. Bills of Lading linked to firm identifiers, and construct an event-time variable that captures the time since the first exposure to a disaster.

The baseline estimating equation is:

$$Y_{it} = \sum_{k \neq -1} \beta_k \cdot \mathbb{I}(t - T_i = k) \cdot D_i + \alpha_i + \delta_t + \varepsilon_{it} \quad (5)$$

where:

- Y_{it} is the outcome of interest for firm i in quarter t, specifically the export value standardized relative to the control group mean.
- D_i is a treatment indicator equal to 1 if firm i is ever treated, and 0 otherwise.
- T_i denotes the treatment quarter for firm i, and k indexes the time relative to treatment ($k = -1$ is omitted as reference).
- α_i are firm fixed effects capturing time-invariant firm heterogeneity.
- δ_t are time fixed effects capturing common shocks across quarters.
- ε_{it} is the error term, clustered at the firm level.

The outcome is measured as:

$$\text{Standardized Exports}_{it} = \frac{\text{Export Value}_{it} - \mu_{\text{control}}}{\mu_{\text{control}}} \quad (6)$$

where μ_{control} is the average export value among untreated firms in the sample. We restrict the control mean to strictly positive export observations to avoid skewing the denominator with zero export records.

4.2 Estimating the Indirect Effect on U.S. Importers

We next examine how natural disasters abroad indirectly affect U.S. firms by disrupting their foreign suppliers. The treatment is defined as a disaster hitting at least one foreign supplier of a U.S. firm. To isolate this indirect channel, we control for disasters occurring in the U.S. firm's own location, thereby separating supplier-origin shocks from local ones.

Our main specification is an event-study model:

$$Y_{it} = \sum_{k \neq -1} \beta_k \cdot \mathbb{I}(t - T_i^{\text{supplier}} = k) \cdot D_i^{\text{supplier}} + \sum_{\tau=0}^{4} \delta_\tau \cdot \text{DirectDisaster}_{i,t-\tau} + \alpha_i + \delta_t + \varepsilon_{it} \quad (7)$$

where:

- Y_{it} is the outcome of interest for U.S. firm i in quarter t (e.g., total imports or importer performance). To account for the mechanical reduction coming from the direct effect, we exclude imports from affected suppliers through out all our window of analysis.
- D_i^{supplier} is a treatment indicator equal to 1 if firm i is exposed to a disaster through one of its suppliers.
- T_i^{supplier} is the quarter of first exposure via a foreign supplier.
- $\text{DirectDisaster}_{i,t-\tau}$ are leads of direct shocks to the U.S. firm's own location, to control for local confounders.
- α_i and δ_t are firm and time fixed effects, respectively.
- ε_{it} is the error term, clustered at the firm level.

This specification allows us to estimate the dynamic response of U.S. firms to supply chain disruptions caused by foreign disasters, while accounting for possible contemporaneous or lagged domestic shocks. The coefficients β_k trace out the path of the indirect effect over time, with $k = -1$ omitted as the reference period.

4.3 Heterogeneous Effects by Ownership: The Role of Affiliates

To explore whether U.S. firms with foreign affiliates are differentially affected by supply-side shocks, we extend the indirect effect analysis by interacting the treatment with an indicator for ownership links. The idea is that multinationals may be better positioned to absorb disruptions through internal reallocation or enhanced coordination with affiliated suppliers.

We estimate the following event-study specification:

$$\begin{aligned} Y_{it} = \sum_{k \neq -1} \Big[& \beta_k \cdot \mathbb{I}(t - T_i^{\text{supplier}} = k) \cdot D_i^{\text{supplier}} \\ & + \theta_k \cdot \mathbb{I}(t - T_i^{\text{supplier}} = k) \cdot D_i^{\text{supplier}} \cdot \text{Affiliate}_i \Big] \\ & + \sum_{\tau=0}^{4} \delta_\tau \cdot \text{DirectDisaster}_{i,t-\tau} + \alpha_i + \delta_t + \varepsilon_{it} \end{aligned} \tag{8}$$

where:

- Affiliate$_i$ is an indicator equal to 1 if U.S. firm i has an ownership link with its foreign supplier.

- All other terms are defined as in the previous subsection.

This specification allows us to test whether the indirect effect of supply disruptions differs for multinationals relative to purely arm's-length importers. The coefficients θ_k capture the additional (or mitigated) response for firms sourcing from affiliates. A muted response among affiliated firms would suggest that internal sourcing relationships provide greater resilience to natural disaster shocks in global supply chains.

5 Results

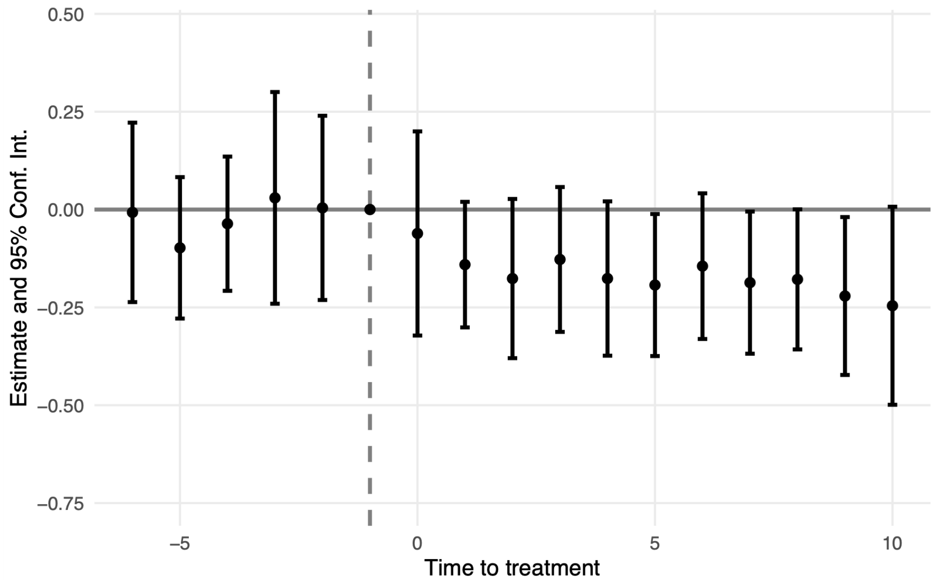
5.1 Direct Effect

We define as our treatment variable the number of quarters since the first exposure to a natural disaster on foreign firms that supply inputs to US firms. Firms not yet treated in a given quarter contribute to the control group. We include fixed effects for firm and quarter to absorb unobserved heterogeneity and macroeconomic shocks, respectively.

Figure 4 shows the dynamic effect of natural disasters on the export value of foreign firms that supply intermediate inputs to U.S. firms. We find no evidence of pre-trends, supporting the identifying assumption. Following a disaster, exports decline sharply and persistently. The point estimates imply a reduction of about 20–25 percent in export value relative to the control group, with effects lasting several quarters. This suggests that natural disasters significantly disrupt the ability of foreign suppliers to continue exporting intermediate goods to their U.S. buyers.

These results confirm a sizable first-stage effect: supply-side shocks from natural disasters abroad disrupt trade flows through firm-to-firm linkages, reducing the availability of imported intermediates. This motivates our downstream analysis, where we study how such disruptions transmit to U.S. importers via both direct and indirect exposure to affected suppliers. Preliminary results in Appendix B further support this pattern, showing a negative effect on the growth of total imports among U.S. firms exposed to affected suppliers. The next section of the appendix builds on this first stage to examine the broader implications for importer performance.

Figure 4: Event Study: Export Value Before and After Natural Disasters



Notes: This figure shows the direct effect of the first exposure to extreme natural disasters on foreign exporters' sales around.

6 Conclusions

This paper presents the construction of a novel dataset to study how disruptions in international production networks propagate across sectors and countries. To examine this question, we build on the approach of Alviarez et al. (2021) and combine four rich micro-level sources: (1) financial data on U.S. public firms from Compustat; (2) the universe of U.S. maritime import transactions from the Bills of Lading (2007–2020); (3) firm-level ownership linkages from Orbis; and (4) geo-coded data on natural disasters, including precise location, timing, and severity.

The resulting dataset offers a comprehensive view of U.S. firms' participation in global value chains, including both U.S. multinationals and affiliates of foreign MNCs operating domestically. While each of these data sources has been used separately in previous research, our contribution lies in merging them into a unified framework. To our knowledge, this is the first effort to link these four datasets at the firm level, enabling a more granular analysis of how supply-side shocks transmit across borders through firm-to-firm connections.

Using this dataset, we show that natural disasters in supplier regions lead to sizable and persistent declines in the export value of affected foreign firms, suggesting meaningful supply disruptions. These shocks propagate downstream: U.S. importers connected to affected suppliers experience reduced import growth, particularly when the relationship is within the same ownership structure. Finally, we document that ownership linkages amplify exposure to shocks, as firms with affected affiliates show larger declines in performance relative to non-affiliated peers. Taken together, our results underscore the importance of production linkages and multinational networks in shaping the transmission of international supply shocks.

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A Geocoding Methodology and Quality Assessment

In this appendix we show the quality assesment of our geocoding algorithm. Results are displayed in Table 6. Bing provides coordinates for 99.8% of the searched addresses. Of the 469,742 U.S. addresses geocoded, 85.2% show high confidence and 85.3% have good (unambiguous) match codes. Additionally, 9.3% of addresses fall inland, and 90.6% of returned addresses match the input country. Geocode quality is lower for foreign partners, as expected given the complexity of international addresses.

Table 6: Geocode Quality Assessment (%)

	US Importers	US Foreign Partners	Total
Geocoded	469,742 (99.9)	993,587 (99.8)	1,463,329 (99.8)
Confidence level			
High	400,780 (85.2)	678,749 (68.2)	1,079,529 (73.7)
Medium	61,802 (13.1)	300,486 (30.2)	362,288 (24.7)
Low	7,160 (1.5)	14,352 (1.4)	21,512 (1.4)
Match Codes			
Good	387,054 (85.3)	514,962 (51.7)	902,016 (61.6)
Ambiguous	42,924 (9.1)	253,862 (25.5)	296,786 (20.2)
Up Hierarchy	39,764 (8.5)	224,763 (22.6)	264,527 (18.0)
In Land	467,359 (99.3)	979,759 (98.4)	1,447,118 (98.8)
Same Country	426,406 (90.6)	833,695 (83.7)	1,260,101 (86.1)
Total	470,435	995,568	1,466,003

Notes: This table reports the quality of the geocoding procedure. The first row shows the total number of addresses successfully geocoded. Rows 4–7 report confidence levels. Rows 8–10 show match code distribution. Row 11 indicates whether coordinates lie inland, and the final row reports country match accuracy between input and returned values.

B Additional Empirical Results

This appendix presents complementary evidence on the effects of natural disasters on trade flows and firm outcomes. We explore three additional dimensions: the impact on quantities, the indirect effects on U.S. importers, and the role of multinational ownership.

B.1 Direct Effects on U.S. Suppliers

To complement our baseline analysis in values, we estimate an event-study specification using growth in export quantities as the outcome:

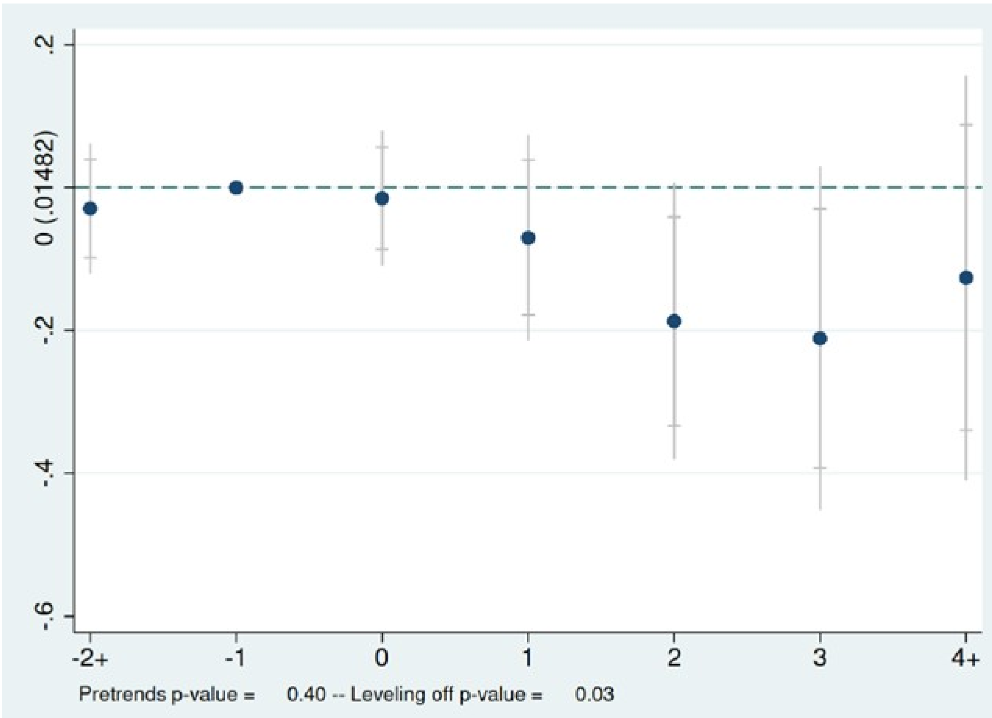
$$g^X_{is,t} = \alpha + \alpha_{is} + \alpha_t + \sum_{\tau=-F}^{L} \beta_\tau \, \text{Dis}_{l_{(i)},t^*_{(i)}-\tau} + \epsilon_{is,t} \tag{9}$$

where $g^X_{is,t}$ denotes the quarterly growth in export quantity for supplier i in sector s, and

$\text{Dis}_{l_{(i)},t^*_{(i)}-\tau}$ indicates whether location l experienced a disaster τ quarters before firm i's treatment quarter $t^*_{(i)}$. The specification includes firm-sector and time fixed effects.

The results are shown in Figure 5. We find that disasters lead to a significant and persistent decline in export quantities, reinforcing our value-based findings.

Figure 5: Event Study: Growth in Export Quantities Following Disasters



Notes: This figure shows the effect of extreme natural disasters on foreign exporters' exported output.

B.2 Indirect Effects on U.S. Importers

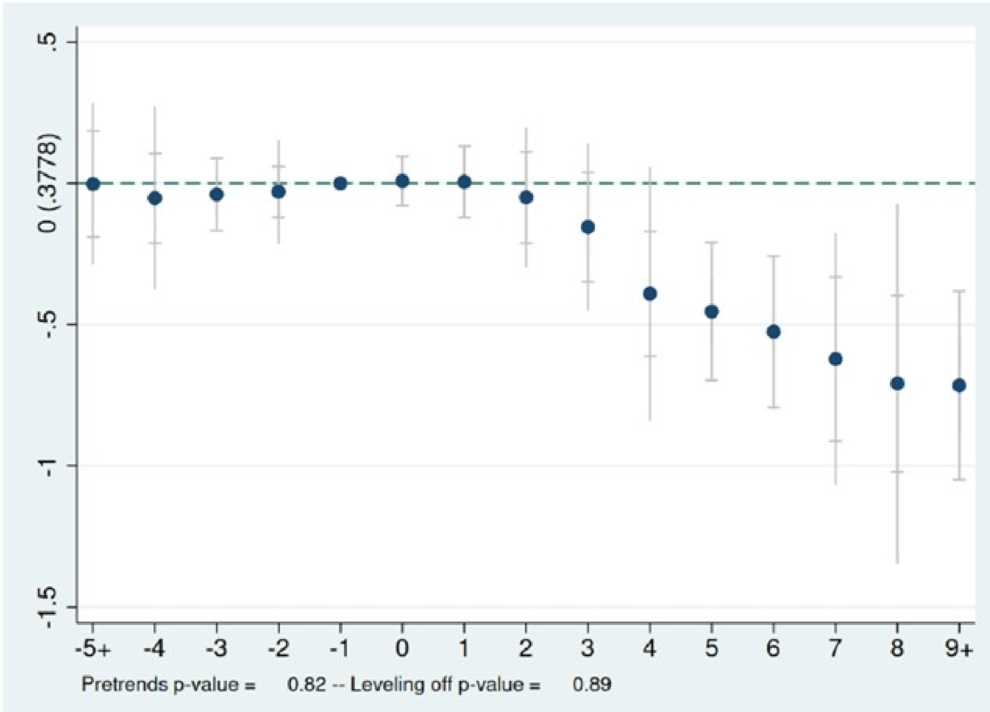
Next, we investigate the indirect effects of foreign disasters on U.S. importers. We estimate the following event-study specification:

$$g^{US}_{is,t} = \alpha + \alpha_{is} + \alpha_t + \sum_{\tau=0}^{4} \delta_\tau \, \text{Dis}_{l_{(i)},t^*_{(i)}-\tau} + \sum_{\tau=-F}^{L} \beta_\tau \, \text{PartnerDis}_{l_{(i)},t^*_{(i)}-\tau} + \epsilon_{is,t} \qquad (10)$$

where $g^{US}_{is,t}$ is the growth in U.S. imports from supplier i in sector s, $\text{Dis}_{l_{(i)},t^*_{(i)}-\tau}$ captures domestic disasters, and PartnerDis refers to disasters hitting the foreign suppliers of U.S. firms.

Figure 6 shows that U.S. import growth declines following disasters affecting foreign partners, indicating a clear indirect impact.

Figure 6: Event Study: Impact on U.S. Import Growth via Foreign Partner Disasters



Notes: This figure shows the effect of extreme natural disasters on foreign importers' imported output.

B.3 Ownership Effects

Finally, we study whether multinational ownership structures mitigate or amplify the shock propagation. We estimate the following regression at the firm level:

$$\Delta \text{Sales}_{i,t-1,t} = \alpha_0 + \alpha_1 \text{DisasterHitsFirm}_{i,t} + \sum_{\tau=0}^{1} \beta_\tau \text{ DisasterHitsAffiliate}_{i,t-\tau} + \eta_i + \lambda_{sat} + \epsilon_{it} \tag{11}$$

where $\Delta\text{Sales}_{i,t-1,t}$ denotes sales growth for firm i, and the key regressors capture disaster exposure of the firm and its affiliates. The model includes firm fixed effects (η_i) and state-year-sector fixed effects (λ_{sat}).

Table 7: Impact of Disasters on Multinational Firms and Affiliates

	(1)	(2)
	Sales Growth ($t{-}1$, t)	
	Manufacturing	All sectors
Disaster hits firm (t)	-0.0312[a]	-0.0220[a]
	(0.0043)	(0.0028)
Disaster hits one afilliate (t)	-0.0057[b]	-0.0052[a]
	(0.0029)	(0.0017)
Disaster hits one afilliate (t -1)	0.0012	0.0015
	(0.0027)	(0.0016)
Firm FE	Yes	Yes
IndustryXyears effects	Yes	Yes
Observations	334,315	1,513,417
R^2	0.229	0.219

Notes: The table shows the effect of natural disasters on firm sales growth. The first column shows the effect on manufacturing firms, and the second column shows the effect on all firms. The first set of rows shows the direct effect of natural disasters on a given firm. The second set of rows shows the transmission of an exposed multinational affiliate to a natural disaster to a multinational firm. The third set of rows shows the lag of the transmission term. All specifications include firm fixed effects and industry/year fixed effects.

The results in Table 7 indicate that both direct and affiliate-level exposures significantly affect sales growth, highlighting the role of intra-firm networks in shock propagation.