Trade Networks and Natural Disasters: Diversion, not Destruction

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Abstract

We study how international trade networks react to natural disasters. We combine exhaustive firm-to-firm trade credit and disaster data and use a dynamic difference-in-differences identification strategy. We establish the causal effect of natural disasters abroad on the size, shape and quality of the French exporters' international trade networks. We find evidence of large and persistent disruptions to international buyer-supplier relationships. This leads to a restructuring of the trade network of largest French exporters and a change in trade finance sources for affected countries. We find strong and permanent negative effects on French suppliers' trade credit sales to affected destinations. This effect operates exclusively through a reduction in the number of buyers, particularly among those with good credit ratings. This induces a negative shift in the distribution of the quality of firms in the destination affected by the natural disaster. On the supplier side, we find that large multinationals restructure their network towards buyers in unaffected destinations. Trade network restructuring is higher for large multinationals trading more homogeneous products.

JEL classification: E32, F14, F23, F44, L14

Keywords: Firm Dynamics; Trade Networks; Natural Disaster.

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1 Introduction

Cross-border buyer-supplier relationships is a costly investment for both parties and disruptions to those international trade linkages carry high economic costs. Since the 1970's, the frequency and severity of natural disasters have increased. This has led to wide-scale destruction of public infrastructures, physical capital and durable consumption goods. If natural disasters disrupt durably international buyer-supplier relationships, the economic recovery in the affected countries will take longer and be more costly. The shock will also propagate across borders through global value chains as suppliers in unaffected countries may bear some of the costs. In this paper, we study the resilience of trade networks to natural disasters.

A natural disaster affects international trade networks through a combination of damage to the country production apparatus and damage to the country transport infrastructure. Damages in terms of GDP can be dramatically high, greater than 65% of the affected country's GDP for the most damaging ones in the top quartile. This lowers productivity in the affected destination and increases trade costs with the rest of the world. Standard models of trade with heterogeneous suppliers (Melitz, 2003), heterogeneous buyers (Antras et al., 2017), or both (Bernard et al., 2018), yield a few basic predictions. The combination of increased trade costs and decreased efficiency should lead to fewer matches between buyers and suppliers. Less firms will be productive enough to pay the additional costs to take part in international trade. The effect on the characteristics of the buyers that make up the supplier's network is more ambiguous. A higher trade cost faced by affected buyers should lead to more selection effect and therefore to an increase in quality (in terms of productivity and financial health) of "surviving importers". The negative productivity shock to all potential buyers should lead to a lower quality among incumbent buyers. Still, larger, i.e. more flexible, suppliers and buyers have more opportunities to divert their trade to unaffected countries.

To test these theoretical predictions, we use novel firm-to-firm trade credit data from one of the top three international credit insurers (Coface). We pair data on French exporters between 2010 and 2019 with exhaustive worldwide disaster data from EM-DAT. We then estimate the effect of natural disasters on various firm-level outcomes, describing the size, shape and quality of the French exporters' international trade networks. We use a dynamic difference-in-differences identification strategy. We employ the De Chaisemartin and D'Haultfoeuille (2020) estimator and provide estimates that are robust to heterogeneous treatment effects. Within that framework, we control for supplier-time shocks and geographical region-sector-time shocks.

We find evidence of large and persistent disruptions to international buyer-supplier relationships. This leads to a restructuring of the trade network of largest French exporters and a change in trade finance sources for affected countries. French suppliers decrease their trade credit sales to affected countries. After two years, trade credit exposure has declined by 10.5% (€27,000). Suppliers reduce their trade credit exposure mostly through the extensive margin by reducing their number of clients rather than exposure per client. The number of clients decrease by 8.4% (0.21 buyers) after 24 months. This fall in the number of buyers is persistent, as we find a decrease of about 0.81 after five years. This effect is associated with a decrease in the average quality of the remaining buyers. When differentiating across credit ratings at the time of the disaster, we find that the fall is greater for buyers of medium to high quality. Those are typically larger firms due to Coface rating methodology. Moreover, disasters are not followed by a rise in insolvencies in affected destinations. On the supplier side, we also find that larger firms exhibits greater sensitivity to natural disasters. Suppliers above the tenth decile of size (measured by their initial worldwide number of buyers or trade credit sales) drive most of the observed average effect of natural disasters. At the same time, suppliers with greater local presence in the affected country (from ten buyers) are the ones to experience the greatest losses. We interpret these two results as reflecting the lower opportunity cost for bigger suppliers to switch away from the affected country without fully loosing access to this export market. They have already access to a well-structured network of alternative buyers in other destinations without disbursing additional costs. An analysis at the supplier level provides further evidence of this heterogeneous reaction. The number of buyers under trade credit terms declines persistently while the amount of trade credit flows declines only temporarily and global exports follow a similar albeit more noisy pattern. It is easier for large multinationals with already a wide range of destination countries to divert the extra trade to other destinations and already-existing buyers. It will also be easier for them to use alternative types of trade financing thanks to their relatively stronger market power. Compounding this mechanism, we find that multinationals that operate in sectors with lower output specificity (wholesale, final consumer goods or services, and generic intermediate goods) lose more buyers (between 0.77 and 2.0 extra losses) than those in high output specificity sectors. *Overall, our results indicate that natural disasters mostly induce a reshaping of the trade networks of the largest exporters and a diversion of inter-firm trade finance away from affected markets rather than a permanent destruction of trade.*

Related Literature

We contribute to the literature on the propagation of shocks in international production networks. We are closely related to the literature that leverages natural disasters as exogenous shocks to production networks. Our contribution relative to this literature is three-fold. First, we use data on all large natural disasters between 2008 and 2020 rather than focusing on a specific event. Second, our data is not restricted to foreign affiliates, publicly traded firms or trade in goods. It covers a much more common type of cross-border linkages: goods and services sold under trade credit. Finally, while most of the literature focuses on how the network contributes to the propagation of the shock, we focus instead on how the network itself is affected by the shock. Boehm et al. (2019) show that relationships between US affiliates and Japanese parent companies were mostly resilient to the 2011 Tohoku Earthquake. They show that the earthquake caused a significant drop in sales of Japanese firms to their US affiliates over the short term. This lead to major disruptions of production processes in the US, highlighting shock propagation through production linkages. However, they show this effect is only short-lived. It does not endanger the relationship between the firm and its affiliate over the long-term. In contrast, we find a persistent effect (beyond five years) of natural disasters. Foreign buyers and French suppliers included in our data set are not locked in a relationship the same way US affiliates of Japanese firms are. The sunk cost associated with regular trade relationships is lower than with foreign direct investment (Helpman et al., 2004). The persistent effect we find would be consistent with a model of forced experimentation as in Porter (1991). Temporary disruptions force some buyers to find new suppliers. Once the disruptions are over, a portion of the buyers may decide not to switch back to their former supplier if the cost of doing so outweigh the benefits.[1] Our work is also closely related to Kashiwagi et al. (2018). They focus on the effect of Hurricane Sandy on the domestic and international production networks of publicly traded US firms. They find short-run propagation limited to domestic supplier & customers without international transmission to their foreign counterparts. Carvalho et al. (2016) study the effect of the 2011 tsunami on Japanese production networks only. They find upstream and downstream propagation, up to the fourth degree of separation. Barrot and Sauvagnat (2016) focus on the production networks of publicly traded US firms but include data on all natural disasters occurring in the US between 1978 and 2013. They find the intensity of the downward propagation to be highly dependent on input specificity. The more specific the input, the harder it is to switch to another other source of input and the greater the consequences for the firm downward on the chain. We extend this result by showing that suppliers of more specific products tend to preserve their networks in affected countries despite natural disasters.

This paper relates to the literature on the adjustment margins of international trade to exogenous shocks. As in Bernard et al. (2018) and Garcia-Appendini and Montoriol-Garriga (2013), we find that the buyer margin is the primary source of adjustment following a large shock. This result contrasts with the mostly intensive–margin effects of the Great Financial Crisis identified in Bricongne et al. (2012) [2] or in Malgouyres et al. (2019) following a large positive technological shock.

Our study also relates to the firm-to-firm trade literature. Lenoir et al. (2019) show that search frictions affect the ability of buyers to identify the most productive sellers on international good markets. In a related study, Martin et al. (2020) find that uncertainty reduces

[1] See Larcom et al. (2017) for empirical evidence of this phenomenon in the London subway system in the aftermath of a strike

[2] More recently, Bricongne et al. (2021) find that most of the adjustment to the 2021 COVID pandemic happened through the extensive margin. Interestingly, they find, in line with our results, that the largest exporters accounted for a disproportionate share of the losses

the rate of formation and separation of seller-buyer relationship, in particular for pairs trading stickier goods. Our study confirms the sluggishness of the reaction to external shocks by sectors producing more relationship-specific goods. We extend this result to services by showing that intermediate business services (consulting, manufacturing services) are much less sensitive than final consumer services (utilities, tourism).

Moreover, our work is related to the literature on trade credits and suppliers' decisions to provide trade credit. Garcia-Appendini and Montoriol-Garriga (2013) find that, during the Great Financial Crisis, firms with high liquidity increased the amount of trade credit offered to their most constrained clients. In a following paper, Garcia-Appendini and Montoriol-Garriga (2020) refine this idea and show that the increase in trade credit from suppliers to their distressed clients is strongly related to suppliers' costs to replace those clients. The harder the buyer is to replace because of high sunk cost in establishing the relationship, the longer the supplier will provide trade credit before bankruptcy. We find a similar effect in the case of a natural disaster: the more specific the relationship, the more resilient it is.

Finally, we also contribute to the literature on the economic effect of natural disasters (Noy (2009), Felbermayr and Gröschl (2014)). El Hadri et al. (2019) find mixed evidence of a negative effect of natural disasters on product level exports from affected destinations. We go further thanks to the disaggregated nature of the data and disentangle the different margins in the trade response to natural disasters.

The rest of the paper is organized as follows. Section 2 presents the data and details our empirical strategy and section 3 shows our baseline results. We conduct further robustness tests in section 4. Section 5 provides a discussion of our empirical results in the context of existing theories of trade and heterogeneous firms. Section 6 concludes.

2 Data and Methodology

We first describe our two main source of data in Section 2.1.1 and 2.1.2. Then, we show some stylized facts from our estimation sample in Section 2.1.3. Finally, we present our empirical strategy in Section 2.2.

2.1 Data

2.1.1 Trade Credit Data

We introduce novel trade credit insurance data from Coface, one of the top three global credit insurers. Trade credit is a specific term of payment for the sale of a good or service from one firm to another. It refers to the credit made by a supplier to its client in the period between the production of the good or service and the payment of the bill. In this article, whenever we use the term supplier, we refer to the firm producing the good or service sold. Whenever we use the term client or buyer, we mean the firm buying the good or service from the supplier. Under trade credit terms, the supplier pays for the production of the good or service and allows its client to delay payment until after the delivery. The payment takes place at the end of a grace period that varies according to each supplier-buyer relationship. To protect itself from potential payment default from the buyer, the supplier may decide to purchase insurance. To do so, it subscribes to a trade credit insurance from an insurer like Coface. In case of default the insurer reimburses the due amount minus a deductible. When Coface insures such transactions, the amount insured is defined as the trade credit exposure of the supplier. Crucially, when the supplier intends to get insured for the export market, *it has to provide its full set of foreign buyers under trade credit terms*. This is done to prevent risk selection. For each supplier, we therefore have an exhaustive list of their buyers under trade credit terms on the export market.

Our dataset includes every French suppliers which have subscribed to a trade credit insurance policy at Coface between 2010 and 2019. Supplier are identified by a French fiscal identifier (siren code). In our study, the basic unit of observation is the supplier-destination dyad which we observe every month. We look at the total amount of insured trade credits, the number of buyers, the average exposure per buyer and the distribution of the Coface internal rating of foreign buyers. We also have information on the amount of exposure requested by the supplier to Coface and the amount granted by Coface. Finally, we also use the number and amount of payment defaults from buyers notified to Coface in each market. We are able to distinguish between the two main types of defaults: insolvency from the buyer and "protracted defaults" (i.e. partial default/payment incidents). Table 1 displays the key summary statistics for the outcome variables, for both supplier-destination dyads (panel A and B) and at the supplier level (panel C). Monthly exposure corresponds to the amount of trade credit insured by Coface for a specific supplier-destination dyad. With a median of €10,000 and a mean of €256,150, the distribution of this variable is highly skewed. The number of buyers per destination is characterised by a large standard deviation (13.5) and a median of 1. It reflects the presence of some suppliers with a very large number of buyers in the sample, compared to some others with few buyers. Payment incidents are rare events, only 23,274 are recorded in our database, although some of those are fairly large (standard deviation of 144,220). Finally, the second part of the table shows that most suppliers included in the sample export to several countries, with a median of five and a mean of eight destination countries. This allows us to control for supplier-time fixed effects in our analysis.

Coface ratings are based on a combination of fiscal data, experts opinions and external rat-

Table 1: Sample Descriptive Statistics

	N	Mean	Median	Std.Dev.
Panel A Supplier-Destination Coface				
Monthly Trade Credit (K EUR)	14,692,164	256.15	10	1929.33
Number of Debtors		2.49	1	13.51
Exposure per Debtor (K EUR)		108.15	50	702.44
Requested Amount (K EUR)		358.93	10	2820.94
Defaults (Number)	23,724	1.04	1	0.20
Amount of Defaults (K EUR)	23,724	39.09	11	144.22
Panel B Supplier-Destination Custom				
Monthly Exports (K EUR)		202.53	20.95	2252.10
Number of HS6 Products		4.16	1.00	12.02
Panel C Supplier level				
Destinations (trade credit)	961,296	8.00	2	13.15
Destinations (exports)		7.91	5	9.17

This table presents summary statistics for our estimation sample. Panel A is computed at the supplier-destination level using Coface data. Panel B is computed at the supplier-destination level using custom data. Panel C is computed at the supplier level. See Appendix D for the details on the computations of those variables.

ings. A rating of 0 is the lowest possible. A rating of 10 indicates that the buyer's "performance solidity is undoubted" [3]. We note that both unrated and the "0" category are not as homogeneous as other rating categories. Unrated firms are made up of both new buyers that haven't been rated yet and buyers whose identity is withheld by the supplier as part of a somewhat rare special type of contract. Firms rated "0" are made up of firms that are either ceasing their activity for any possible reasons or firms that are currently defaulting on their payments.

In addition, Coface collects the sector of activity for every relationships covered by the trade credit insurance. Because the unit of observation in our final database is the supplier-destination pair, we assign to each pair the dominant sector of the supplier in this destination. In other words, we know whether a firm mostly supply car parts (NACE 2931) or provide management consulting services (7022) to a given destination. In order to account for the relationship specificity of each sector, we assign each NACE 4-digit sector a BEC5 code taken from the UN Statistical Division classification by Broad Economic Activity. This allows us to group sectors together based on the amount of coordination required between the buyer and the seller to establish a relationship. Details on the composition of BEC categories can be found in table 5 in appendix E.

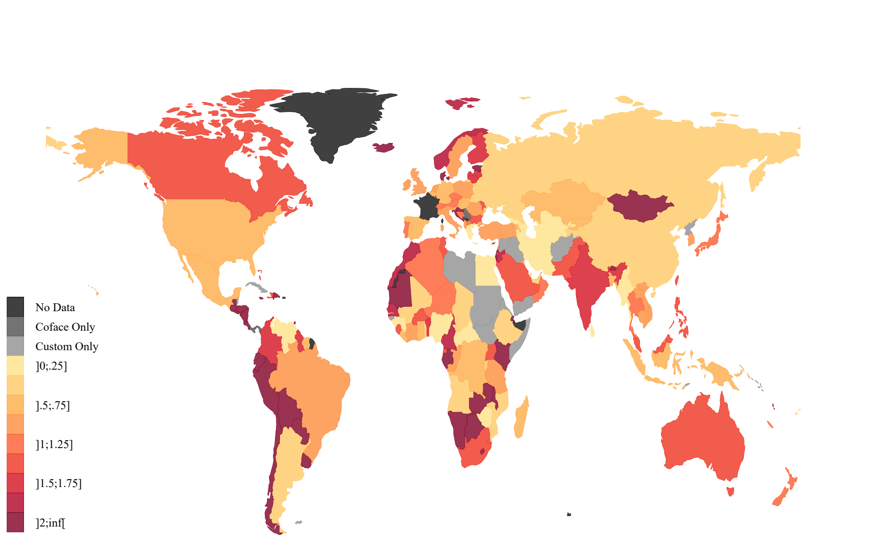
Regarding the representativity of the trade credit data used in the analysis, Muûls (2015) shows that in Belgium there is a large overlap between exporting firms and firms included in Coface database[4]. In the case of French exporters studied here, for the year 2018, the number of firms in Coface database is equal to 4.1% of those in French custom data and 3.2% of firms in FIBEN. However, Coface firms represented 9.4% of produced value added across FIBEN firms. Figure 1 shows the ratio of the amount of trade credit flows recorded in the database with flows recorded in French customs data for French exporters. Almost every country included in French custom data is included in Coface data. The few exceptions are Iran, Cuba, Sudan, Libya and Yemen. The orders of magnitude of trade credit and trade are similar across the two databases. The ratio might be greater than 1 for two reasons: trade credit flows cover both services and

[3] Internal Coface documentation.

[4] "only 200 firms out of more than 13,000 manufacturing firms present in the [Belgium trade database] are not included in the Coface sample."

goods while customs data encompass only goods. Moreover, trade credit exposure is a stock of insured sales without a defined timing for each flow. It also reflects the amount suppliers think they might need for a given period, i.e. their anticipations. As suppliers pay their premium on realized sales (rather than anticipated sales) they may request for larger coverage than the amount actually needed. At the same time, counteracting this effect, the amount of coverage requested affects the premium paid as it affects the risk taken by Coface. Thus, the supplier faces a trade-off and does not request an infinite coverage. Coface also provides incentives to suppliers so that they limit the amount requested to their actual needs as the amount insured defines Coface's capital needs from the regulator's perspectives.

Figure 1: Trade Credit to Customs Data Coverage



NOTE: These figure presents the ratio of Coface trade credit coverage for French exporters with respect to French exports as recorded in customs data.

2.1.2 Disaster Data

For natural disasters, we use the exhaustive EM-DAT database from the Center for Research on the Epidemiology of Disasters (CRED)[5]. The database provides detailed information on natural disasters, including earthquakes, floods, and storms, etc., which occurred worldwide since 1900. The data on disasters is compiled from various sources, including UN agencies,

[5]EM-DAT, CRED / UCLouvain, Brussels, Belgium – www.emdat.be (D. Guha-Sapir)

non-governmental organizations, insurance companies, research institutes, and press agencies. For an event to be recorded in EM-DAT, it needs to lead to 10 or more deaths OR 100 or more "affected" OR to be defined as "declaration of emergency/international appeal". Precise type is provided for each event, through a broad classification and more detailed ones ("Geophysical" > "Earthquake" > "Tsunami"). The exact date of the event, the geographical coordinates and the estimated impact are also included. The impact is measured in deaths, missing, injured, affected people, and estimated damages in US$. We use data from January 2008 to December 2019.

We follow Fratzscher et al. (2020) to build the event variable:

$$D_{j,t} = \frac{\text{reported damage}_{j,t}}{\text{previous year GDP}_{j,t-1}} \tag{1}$$

An event is selected if the reported damage scaled by GDP if $D_{j,t}$ is greater than the median for all disasters and if it is the worst event in this country between 2008 and 2019:

$$E_j = \begin{cases} 1 & \underset{j}{\text{argmax}}(D_{j,t}) \cup D_{j,t} > D^{P50} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

In order to control for potential contamination stemming from an exposure to repeated events, we set as missing any observation in a four-year window around any large disaster event in the country. We define large events as those whose intensity is at least 50% of the worst event. It allows us to build a treated group that is not polluted with some repeated albeit smaller events. Figure 19 in appendix show the selected event per country. The absence of contamination is visible from the different graphs. Appendix A.2 describes the construction of an alternative definition of event, taking the first big event rather than the worst one in a country. We further check that the selected natural disasters do in fact represent a clear break in trend in terms of recorded damage by estimating the impulse response function of damage per GDP ($D_{j,t}$) following an event. We present the results in Figure 20. The only positive and statistically significant coefficient is the one contemporaneous to the recorded event. It shows that the event variable is not capturing damaged caused by previous or future disasters.

Table 2 synthesizes key summary statistics for natural disasters recorded by EM-DAT over the period. We do not record disaster event for 64 countries. Among the 92 recorded events, the most frequent type is hydrological (40 events). The most destructive type is geophysical (USD Mn. 24,848 on average). The description of the main types of disasters can be found in appendix B.1.

Table 2: Sample Descriptive Statistics

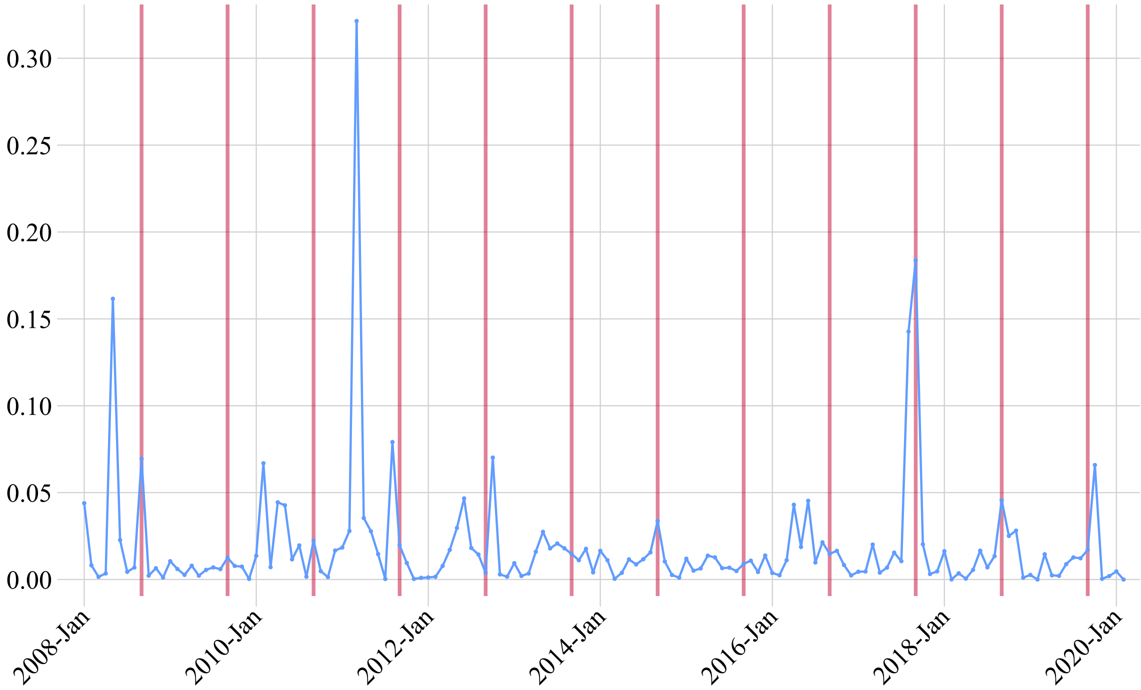
	N	Mean	Median	Std.Dev.
All Disaster Types				
Estimated Damage (USD Mn.)	92	7278.92	500.00	28409.59
Estimated Damage (% GDP)	92	8.73	0.77	30.61
Type = Climatological				
Estimated Damage (USD Mn.)	9	1309.08	500.00	2135.59
Estimated Damage (% GDP)	9	1.19	0.71	1.16
Type = Geophysical				
Estimated Damage (USD Mn.)	11	24848.09	2000.00	62122.61
Estimated Damage (% GDP)	11	15.77	0.97	36.08
Type = Hydrological				
Estimated Damage (USD Mn.)	40	2726.42	438.29	6937.03
Estimated Damage (% GDP)	40	1.64	0.54	3.10
Type = Meteorological				
Estimated Damage (USD Mn.)	32	8609.17	550.00	30235.25
Estimated Damage (% GDP)	32	17.29	1.95	46.29
No Disaster				
Estimated Damage (USD Mn.)	64	4.40	0.00	17.90
Estimated Damage (% GDP)	64	0.00	0.00	0.01

This table presents summary statistics for our estimation sample. Panel A is computed at the supplier-destination level using Coface data. Panel B is computed at the supplier-destination level using custom data. Panel C is computed at the supplier level. See Appendix D for the details on the computations of those variables.

Figure 2 represents the evolution of estimated damage in percentage of GDP in aggregate caused by natural disasters. Hurricane and typhoon seasons are highlighted in red. Total damage to world GDP remains fairly stable since 2008.

Figure 3 shows the geographical distribution of natural disasters events as defined by Equation 2. Countries marked in dark blue compose our permanent control group, while countries in

Figure 2: Natural Disasters



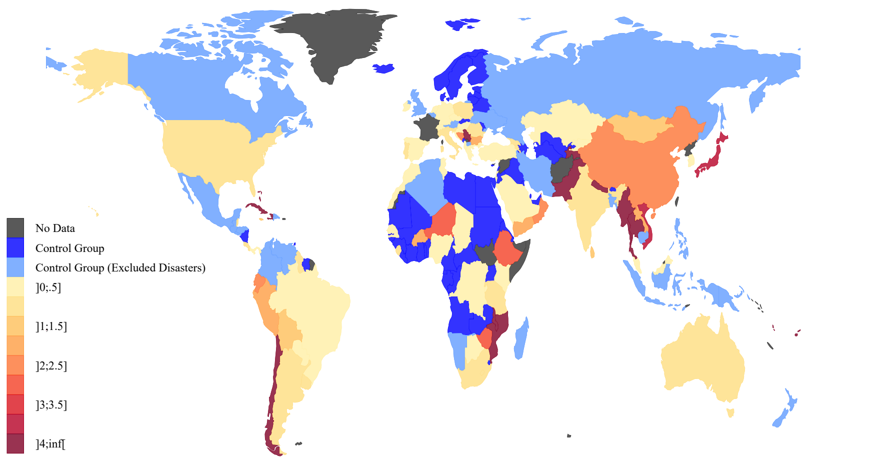
NOTE: These figure presents estimated damage in percentage of GDP caused by natural disasters. The source for the disaster data is EM-DAT. Authors' computations.

light blue are excluded from the treatment group because their worst events are contaminated by repeated events. We recycle their untreated period to increase the size of the control group. Countries in red enter our treatment group in a staggered fashion. The shades of red indicates the severity (in percentage of GDP) of the damage caused by the event. 50% of natural disasters cause damage lower than 0.77 percent of GDP (Table 2).

2.1.3 Estimation Sample

We keep observations for which we have both disaster and trade credit data. The final sample (see Table 3) consists of 14,692,164 observations (i.e. supplier-destination-month triads) over a hundred and twenty months from January 2010 to December 2019. Our data covers the trade credit activity of 9,615 French suppliers. Those suppliers have created 146,833 distinct supplier-destination linkages in 181 different countries. Of those supplier-destination dyads, 29,537 (37%) are never treated. The rest suffers from a natural disaster at some point during

Figure 3: Geographical Distribution of Natural Disasters Events



NOTE: This figure describes the distribution of country between the permanent control group in blue and the treated group in shades of red that is affected at different time. The source for the disaster data is EM-DAT

the sample period. On average about 2% of those dyads are treated each month. The control group used in the estimation is composed of both never treated and not yet treated observations.

Table 3: Sample

Level	N
Months	120 (2010m1-2019m12)
Destinations	181
Suppliers	9,615
Dyads (firms * destination)	146,833
↪ Ever treated	117,296
↪ Never treated	29,537
Observations	14,692,164

NOTE: The estimation sample ends 12 months early when using customs data.

2.2 Empirical Strategy

We want to estimate how natural disasters change the structure of the supplier's network of buyers. As shown in Section 2.1.2, we define the disaster variable as the worst disaster in the country over the period 2008-2019, conditional on the disaster being above the median of all disasters globally over the period and conditional on the absence of other large events four years before or four years after. This allows us to identify the effect of a larger than usual disaster. This is an important criterion for countries exposed to seasonal storms. Concretely, in some cases, pre and post-event periods may be contaminated by other less damaging events. For this reason, we set as missing any observation during which the country suffered from other disasters with an intensity of at least 50% of the worst one. In appendix A.2, we provide results using an alternative definition of the event variable. We take the first event causing damages relative to GDP greater than the median in the whole sample, and at least 50% of the intensity of the worst event in the country over the period. We also mark as missing any observation polluted with events reaching 50% of the damages caused by this first big disaster. Our results are essentially unaffected. The same can be said taking a third definition of our event, modifying the median threshold for selection. In appendix A.5, we provide our main result using the worst disaster in a country, conditional of having a disaster greater than the *third quartile* of damages. Once again, we mark as missing any observation polluted with events reaching 50% of the damages caused by this worst event.

We estimate the effect of this disaster variable on various outcomes that characterise this network (e.g. the number of buyers in the affected country, the overall amount of exposure or the average exposure per buyer, etc.). We aim at capturing the following generic relationship:

$$Y_{f,j,t} = \sum_{k}^{K} \beta^k \times \mathtt{DISASTER}_{j,t-k} + \gamma_{f,t} + \nu_{r(j),s(f),t} + \epsilon_{f,j,t} \tag{3}$$

Where Y is some variable describing the trade network outcome of supplier f in the destination country j at period t, k periods after the occurrence of a disaster. The change of Y is determined by some time varying components ($\gamma_{f,t}$ and $\nu_{r(j),s(f),t}$) at the supplier and the region-sector level, common to certain groups of observations regardless of their treatment status. Those could be the business cycle in the destination country or supplier-specific shocks. The estimation of β^k is the primary focus of this paper. We expect the overall impact of a disaster to be negative ($\beta^k < 0$ for $k \geq 0$) and vary in time relative to the disaster (indexed by k) as firms adjust. Additionally, we expect some heterogeneity in the ability or willingness of firms to adjust. We explore this by doing the same estimation over different sub-samples constructed around firms' specific characteristics. Suppliers with a large global footprint benefit from a network that includes buyers in unaffected countries. They may be able to pivot away from the disaster-stricken country so we expect that β^k will vary depending on the sub-sample arranged by firms' decile of size. Finally, suppliers that supply more specific goods or services, such as intermediate products tailored to a given buyer, incurred a much higher sunk cost in establishing the initial relationship than suppliers selling non differentiated products. Switching suppliers will prove more costly for those suppliers. We, therefore, expect that higher specificity moderates the effect of a disaster with decreasing β^k based on the level of specificity in each sub-sample.

To estimate our β^k, we rely on a Difference-in-Differences strategy and exploit the fact that some countries are hit by natural disasters at different times or not at all. We use the De Chaisemartin and D'Haultfoeuille (2020) estimator. It accounts for the weighting issues generated by standard difference-in-differences estimator (see for instance Callaway and Sant'Anna (2019) and Goodman-Bacon (2018)). In particular, they show that the coefficients identified by the canonical two-way fixed effect (TWFE) model are a combination of the actual treatment effect and weights. In the case of a staggered design, the TWFE mechanically computes negative weights for some periods and groups. In some cases it can result in negative estimated coefficients when the treatment effects are in fact positive. This problem is more acute in the presence of treatment effect heterogeneity, either across groups or across periods. The identifying assumption is that suppliers operating in affected and unaffected countries would have had the same outcome in the absence of a natural disaster. This assumption likely holds for two reasons: first large natural disasters are exogenous to local economic activity in the short term, second, we do not detect any significant differences between non treated and not yet treated observations.

We follow De Chaisemartin and D'Haultfoeuille (2020) to estimate the effect of disasters and use this estimator:

$$DID_k = \sum_{t=k+2}^{T} \frac{N_t^k}{N_{DID_k}} DID_{t,k} \tag{4}$$

Where

$$DID_{t,k} = \underbrace{\sum_{f,j:E_j^d=t-k} \frac{1}{N_t^k}(\overbrace{\tilde{Y}_{f,j,t}}^{\text{Now}} - \overbrace{\tilde{Y}_{f,j,t-k-1}}^{\text{Before}})}_{\text{Treated}} - \underbrace{\sum_{f,j:E_j^d>t} \frac{1}{N_t^{nt}}(\overbrace{\tilde{Y}_{f,j,t}}^{\text{Now}} - \overbrace{\tilde{Y}_{f,j,t-k-1}}^{\text{Before}})}_{\text{Not yet Treated}} \tag{5}$$

Where f indexes suppliers, j the destination country, t the monthly (or yearly) dates, k the month (or year) relative to the disaster. $\tilde{Y}$ is the residualized outcome over a set of fixed effects: either sector-region-month or firm-month. N_t^k the number of firm-destination links treated at date $t-k$, $N_{DID_k} = \sum_t N_t^k$ and E_j^d the date of the disaster

Each treatment effect $DID_{t,k}$ is estimated with OLS. The De Chaisemartin and D'Haultfoeuille (2020) Difference-in-Differences estimator allows to estimate dynamic effects across k periods following the disaster. It also absorbs permanent differences between destinations. To account for time varying shocks, we residualize the outcome variables over region-sector-time and firm-time fixed effects prior to the estimation. The former accounts for common shocks across suppliers in a given market (here a NAF 4-digit sector in large geographical region). The latter accounts for common shocks across the various destination countries of a given suppliers. Identification results from comparing a firm outcomes across all of its export destinations after absorbing time-varying destination market factors. This specification limits the sample to supplier present in two or more destinations and to markets that source from a least two suppliers. We cluster the standard errors at the region-sector level. It allows for autocorrelation of the error term within regional sectors. It also allows for correlation across buyers within those regional sectors.

Throughout the paper, we show the results of estimating DID_k to evaluate the time-varying impact of natural disasters on the international network of French suppliers. As a baseline, we estimate DID_k with the outcome variables $\tilde{Y}$ measured in level (amount in euros, number of buyers, etc.). This yields the average change ΔY in affected destinations relative to unaffected destinations. It does not require the omission of observations taking the value zero as opposed to using the log of those outcomes. We expect a higher frequency of zero flow to the affected destination in the aftermath of the disaster. Dropping those observations would bias $DID_{t,k}$ toward zero. We provide results robust to functional forms mis-specification in Section 3.1.3.

3 Results

We first present our main results in section 3.1 on the effect of natural disasters on the size of suppliers' network in affected countries. We then explore the effect on the shape and quality of the network in Section 3.2. In 3.3, we examine to what extent some suppliers can better adjust to disasters. Finally, in 3.4, we provide a measure of the suppliers' aggregate response to a natural disaster in one of their destinations

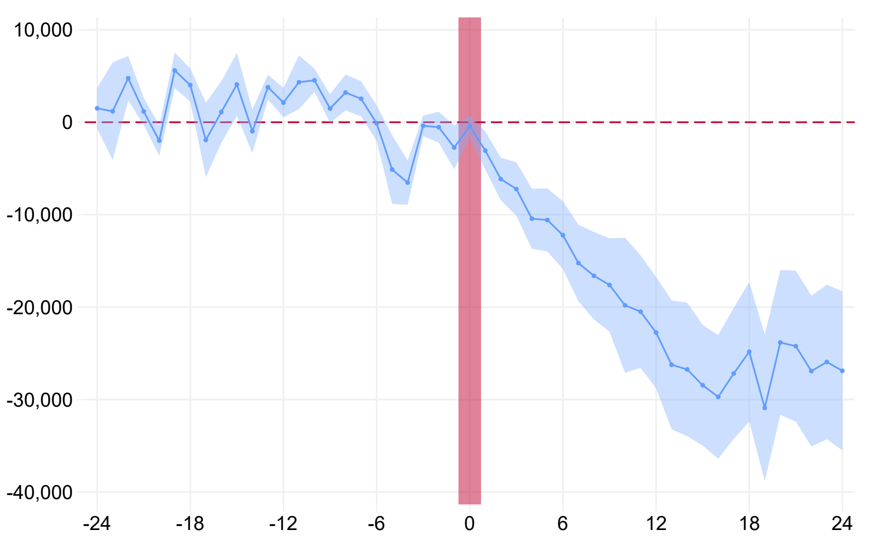
3.1 Main Results

We first present our result on the effect of natural disaster on the use of trade credit by French suppliers selling in affected destinations. In Figure 4, we plot the time varying effect of a disaster on French suppliers' trade credit exposure to clients in affected countries. The outcome variable is the amount in euros of trade credit exposure for a given supplier in the affected country. $k = 0$ marks the month of the disaster. The pre-shock trend is estimated to be close to zero. After the disaster, exposure decreases by €22,700 after 12 months and €27,000 after 24 months. The average trade credit exposure is €256,150 (P50 = 10,000). The total loss after 24 months represents a 8.9% (12 months) and a 10.5% (24 months) decrease in trade credit exposure to the affected destination relative to the sample mean.

3.1.1 The decline is entirely explained by the "buyer margin"

We can decompose this effect in an extensive and intensive margin. The disaggregated nature of the underlying trade credit data allows us to compute both the probability to start exporting

Figure 4: Effect of Natural Disasters on Exposure



NOTE: These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 5. We include here supplier-time and region-sector-time fixed effects. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue lines. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2008 and 2019, we consider only the largest one. The outcome variable is the amount in euros of trade credit insurance for a given supplier in the affected country. See Appendix D for the details on the computations of this variable.

under trade credit terms with insurance in the country and the "buyer extensive margin" i.e. the number of buyers using trade credit terms in the destination country. To measure the effect on the intensive margin, we compute the average trade exposure per trade credit buyer in the destination country. We provide details on the computations of those variables in Appendix D.

In Figure 5, we show that the impact is driven by the buyer margin, i.e. the number of clients rather than the exposure per client. The effect increases from about from -0.16 buyers after 12 months to -0.21 buyers after 24 months and is robust to the inclusion of both supplier-time fixed effects and sector-region-time fixed effects (Figure 5a). The average number of buyers in the sample is 2.49 (P50 = 1). This represents a 8.4% decline in the number of buyers using trade credit 24 months after a disaster. Meanwhile, we find no impact on the intensive margin (Figure 5c). Looking at the probability to export under insured trade credit terms, we find a slightly positive effect, with a 2% increase in the probability to export under insured trade credit terms (Figure 5b). This increased probability is however absent from customs' trade in goods data

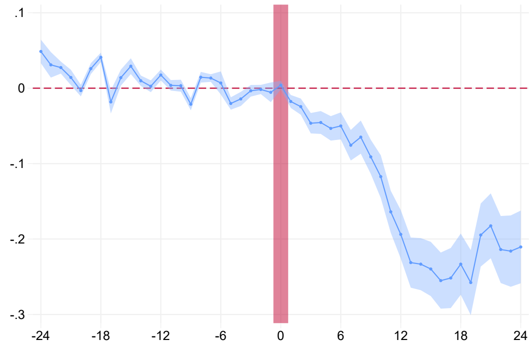
(Figure 26). We interpret this as an increase in demand for trade credit from some buyers which translate into a higher probability of having at least 1 insured buyer in the affected destination. We provide a further decomposition of the extensive margin effect in Section 3.1.3. It confirms that the negative average effect on the number of buyers originates from a lower probability of having many (more than 10) buyers.

In section B.2 in appendix, we focus on the buyer margin and the heterogeneity in terms of disasters, following EM-DAT classification. We find that geophysical events (e.g. earthquake), while being the most destructive (see table 2), are also the events that cause the steepest fall in the number of buyers in the affected country. After 2 years, there is a decrease of -1.4 buyers following a geophysical event. Meteorological (e.g. typhoon) and climatological (e.g. drought) events tend to cause a smaller response even though negative. For hydrological events, the small but positive effect should be interpreted in line with the limited damage typically caused by this type of disaster (see table 2). Such results reflect the heterogeneity in the extent of damages caused by each type of disaster.

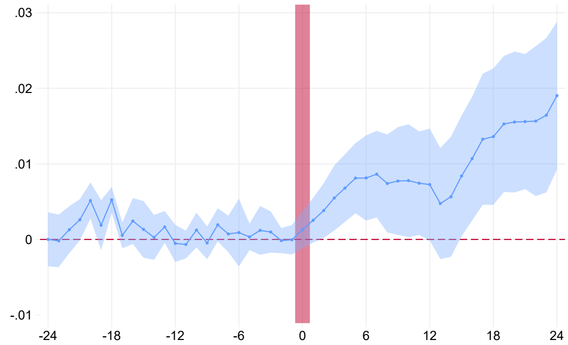
3.1.2 Persistence of the effect after five years

To assess the long run consequences of natural natural, we repeat the same estimation procedure as in Equation 4 and Figure 5a on a sample aggregated at the yearly level. We average the monthly trade credit stocks over the year. We present those results in Figure 6. We find that the number of buyers in the affected country decreases persistently, and doesn't come back to its pre-disaster level within a five-year window. The average loss at this horizon is 0.81 buyers per supplier. Using the alternative definition of a disaster event (Appendix A.3), we see that the orders of magnitude are very similar, with a loss of 1.01 buyers per supplier for the first event. The difference between both estimate is small and each estimate falls within the other's confidence interval. Wee provide additional results with a third definition of our event that selects disasters greater than the third quartile in the whole sample distribution. We see again very similar results (Appendix A.5). We further confirm our result by checking that they do not reflect ex-ante differences between treated and non treated. In Appendix A.4, we repeat the

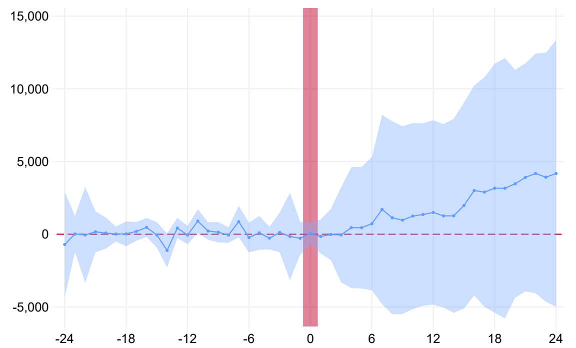
Figure 5: Extensive and Intensive margin



(a) Number of Buyers with Trade Credit



(b) Probability of Export under Insured TC Terms



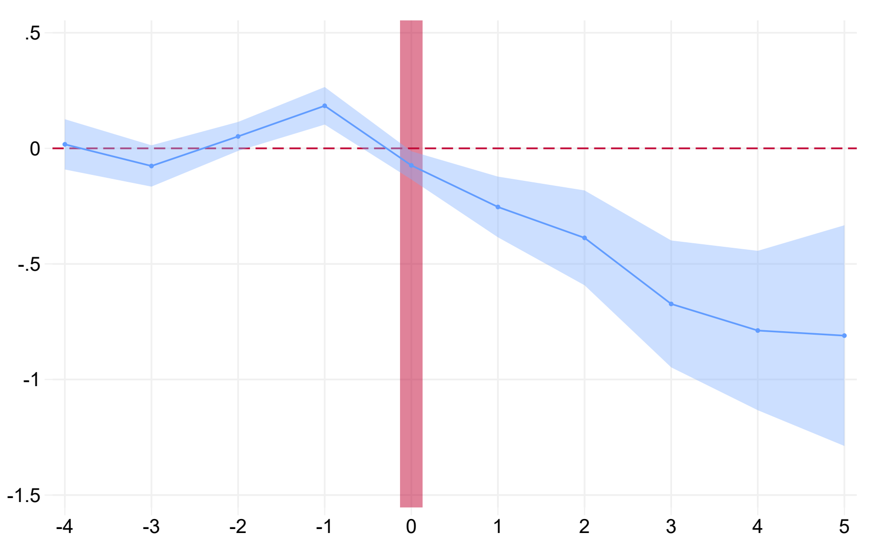
(c) Trade Credit / Number of buyers

NOTE: These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 5. 99% error bands, computed with robust standard errors clustered at the region-sector level, are displayed as blue lines. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2008 and 2019, we consider only the largest one. In Panel 5a, the outcome variable the number of buyers purchasing from the supplier at credit. Results are displayed including a supplier-time and sector-region-time fixed effects. In Panel 5b, the outcome variable is a dummy indicating whether the supplier has at least one trade credit relationship in the affected destination. In Panel 5c, the outcome variable is the average amount of trade credit per buyer in the affected destination. See Appendix D for the details on the computations of those variables.

estimation with our alternative definition of event (first big disaster). This time we exclude the never treated observations and use only the not-yet-treated dyads as control group. We find an even greater effect, with the fall in the number of buyers reaching 2 buyers after 5 years.

Our results are robust to various definitions of the event variable and to potential differences across the treated and non-treated.

Figure 6: Long run effect (yearly data)



NOTE: These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 5 at the yearly level. We include here a supplier-time and sector-region-time fixed effects. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue lines. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2008 and 2019, we consider only the largest one. The outcome variable is the number of buyers of trade credit insurance for a given supplier in a country. See Appendix D for the details on the computations of all LHS variables.

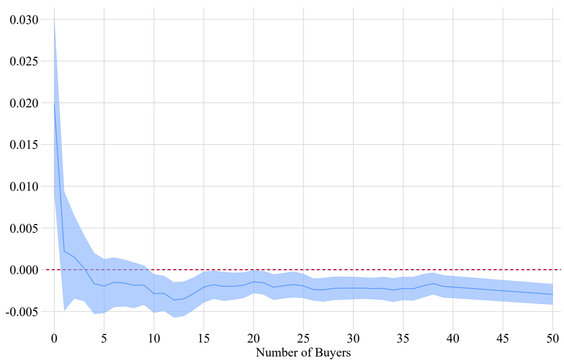
3.1.3 The effect on the extensive margin is concentrated on top of the distribution of buyer per destination

In Section 3.1, we showed that the buyer margin was driving the negative effects of disasters while the country margin (i.e. the probability to have 1 or more buyers in the affected destination) exhibited small but positive effects. To further disentangle the margin through which firms adjust to external shocks, we estimate the effect of a natural disaster on the cumulative distribution of buyers per supplier-destination. It allows us to isolate which part of the distribution of the number of buyers per supplier is most affected. We estimate the same equation as in Equation 4 but we replace the outcome variable with a dummy equal to one for supplier-destinations with a number of buyers greater than x. We repeat this estimation for every possible value of x (from 0 to 50, the 99^{th} percentile) in increments of 1. This method allows to estimate the entire conditional distribution. Importantly, it does not require the outcome to have a smooth conditional density as in quantile regressions (Chernozhukov et al., 2013). [6]

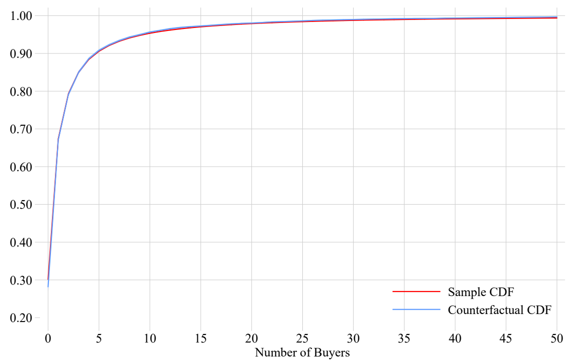
Figure 7a plots the effect on the distribution along the values of the outcome variable, here the number of buyers. We see that the effect measured in our baseline specification is largely explained by a decrease in the probability of having at least 10 buyers or more per destination. The effect on the probability of having at least a single buyer is slightly positive (about two percentage points). A disaster decreases the probability of having more than twelve buyers by 0.3 percentage points and more than fifty buyers by about the same. With a small dip between 10 and 15 buyers, the effect is quite stable until 38 buyers before slightly increasing. We show in Figure 7b that it results in a shift of the cumulative distribution towards the left for any number of buyers greater than 3. In other words, the new distribution of buyer-per-supplier includes a lower number of suppliers with a lot of buyers. Suppliers with a single foothold did not loose it and suppliers with a small local buyer base went mostly unaffected.

Figure 7: Effect of Natural Disaster on the Distribution of Buyers per Supplier-Destination

(a) Distribution Regressions



(b) Counterfactual CDF



NOTE: These figures present estimates of the coefficients DID_k associated with natural disaster events from estimating Equation 4. We include here supplier-time and region-sector-time fixed effects. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue lines. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2013 and 2020, we consider only the largest one. The outcome variable is the number of buyers per supplier-destination. In Panel 7a, we plot the sequence of coefficients from estimating the baseline equation for every value of x. In Panel 7b, we plot the observed CDF in red and the estimated counterfactual CDF in blue. For details on distribution regressions see Chernozhukov et al. (2013).

[6]See Aghion et al. (2019), Goodman-Bacon and Schmidt (2020) or Blanc (2020) for recent applications.

3.1.4 Trade in goods and natural disasters

We've established that natural disasters leads to a lower amount of buyers using trade credit in affected destinations. While the data doesn't allow us to unambiguously determine if the end of a trade credit relationship means the end of the underlying trade relationship, the decrease in the number of buyers using trade credit likely reflects a lower number of domestic firms sourcing from French suppliers. Based on previous work (Garcia-Marin et al., 2020), we know that firms rarely switch away from trade credit. In this section, we use customs data on trade in goods to investigate whether there are any effects on actual cross-border flow of goods. We unfortunately do not have the corresponding data on trade in services. We keep the same specification as before and average the export variables over a three-month rolling window. This sub-sample contains firms that are present in both French customs and Coface datasets. As a consequence it only extends from 2010 to 2018 for the exports of goods. We first estimate the effect on the total value in euros exported by French suppliers to their affected destinations. We then repeat the exercise with the quantities (in kilograms), number of products (at the HS6 level in the 2007 nomenclature) and the unit values (euros per kilogram). We report the result in Figure 8. In panel 8a, we show that the values of the transactions toward the affected destinations experience a clear break in trend around the time of the disaster. The estimate is however relatively small (about €10,000) and noisy. It decreases until 15 months after the disaster, without being fully significant at 1%. It likely reflects strong heterogeneity in the response. In panel 8b we see a small and short-term decline in the quantity exported before a medium-run increase albeit non-significant. The same non-significant increase is visible for unit values in panel 8c. Finally, panel 8d indicates that natural disasters do not lead to a lower number of exported products. We also do not find evidence of an effect on the probability of exporting to a country struck by a natural disaster (Figure 26).

From this last set of results we can see that trade credit stocks are more clearly affected by the disaster than overall export flows, which display a very heterogeneous response to the disaster. Therefore, natural disasters are likely to weigh on the outlook in affected destinations mostly through changes in trade networks and trade financing structure, rather than through changes in aggregate trade levels. While the effect on overall trade flows is limited, the modification of the trusted network of buyers to whom the supplier will extend trade credit is likely to cause ripple effects in the economy. The recent literature has extensively discussed how trade credit is one of the key financing tools for firms, with most financially constrained firms needing it the most (see Minetti et al. (2019), Molina and Preve (2012) among others). Boissay and Gropp (2007) highlight how defaulting on their trade credit is often used by firms to relax their financial constraint. In the Turkish case, Demir et al. (2020) find that a shock to trade credit provisions for importers will propagate downstream in the supply chain and can lead to non-trivial aggregate effects. Therefore, by disrupting credit supply for some buyers in affected countries, natural disasters could create financial disruptions along the supply chain if they were to impact financially constrained buyers strongly involved in the country's supply chain.

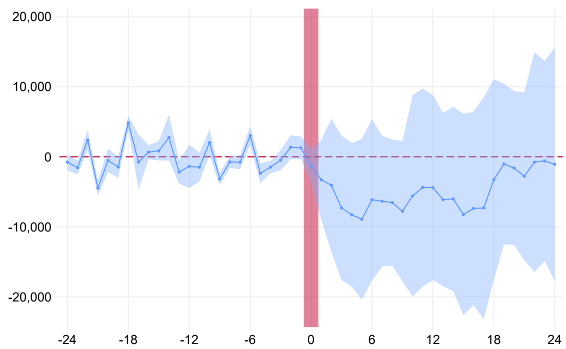
3.2 Natural disasters decrease the quality of the supplier's networks of buyers

We now focus on the effects of disasters on the quality of the supplier's network of buyers in the destination country. We proxy quality with the Coface internal ratings of buyers.

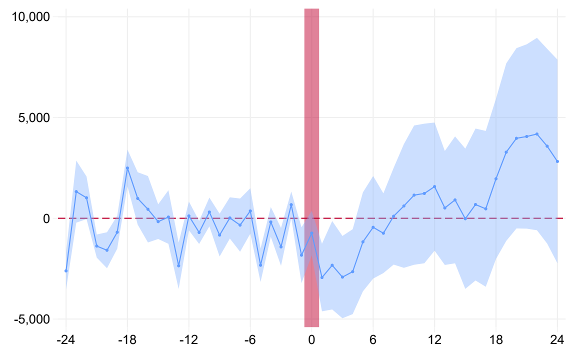
We compute the number of buyers in each rating category: $T^r_{j,f,t} = \sum \mathbf{1}(EXPO_{j,b,f,t} > 0 \cup R_{b,t} = r)$. We estimate the effect of natural disasters on the number of buyers per supplier in each rating category using the same estimator as before, i.e. the De Chaisemartin and D'Haultfoeuille (2020) estimator with region-sector-time fixed effect and supplier-time fixed effect. We find that natural disasters induce a negative shift in the distribution of buyer quality two years after the event. We show the results in Figure 9. The bins in red represent the sample average number of buyers in each rating category. The bins in blue represent the counterfactual average number of buyers per category after subtracting the coefficient from the sample average.

Figure 8: Effects of Natural Disasters on the Export of Goods

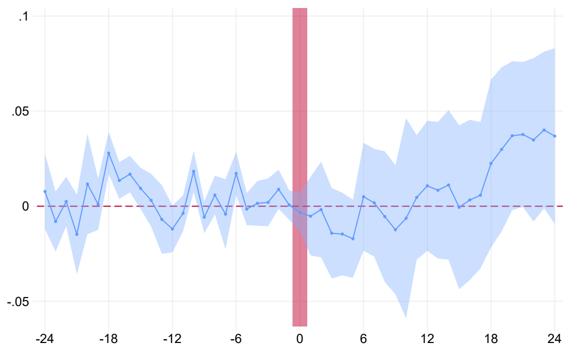
(a) Total Transaction Value (Euros)



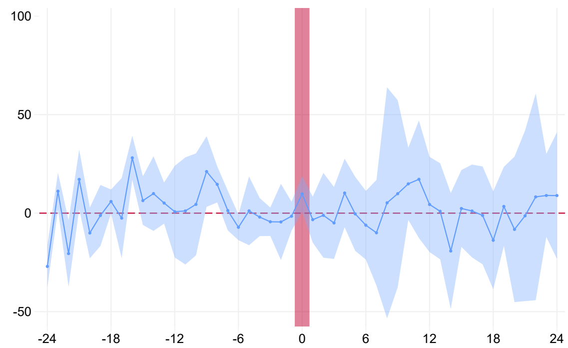
(b) Total Transaction Quantity (Kg)



(c) Unit Value (Euros/Kg)



(d) Number of Products (HS6)

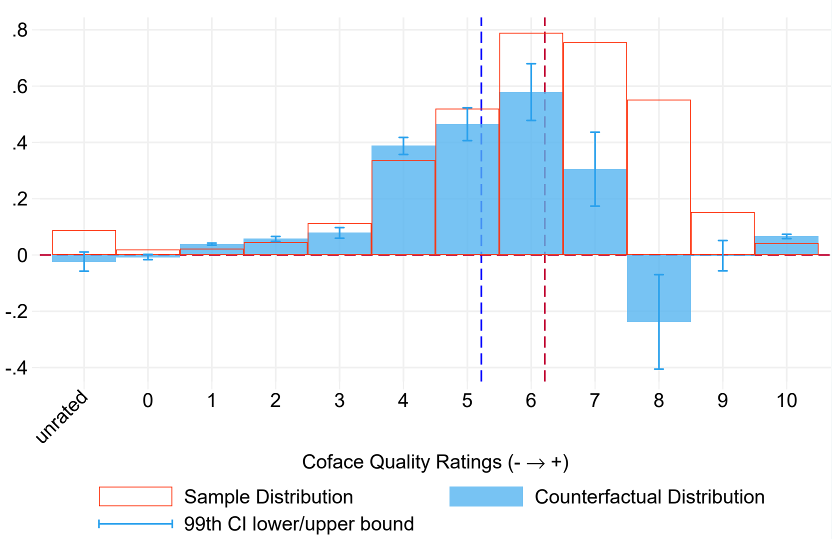


NOTE: These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 5. We include here supplier-time and sector-region-time fixed effects. 99% error bands, computed with robust standard errors clustered at the region-sector level, are displayed as blue lines. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2010 and 2019, we consider only the largest one. In Panel 8a, the outcome variable is the three-month rolling average total value in euros exported by French suppliers to their destination. In Panel 8b, the outcome variable is the three-month rolling average quantity exported in kilograms. In Panel 8c, the outcome variable is the three-month rolling average unit values (euros per kilogram) of the exports. In Panel 8d, the outcome variable is the three-month average number of exported products in each destination defined at the HS6 level in the 2007 nomenclature. See Appendix D for the details on the computations of those variables.

We find that in the aftermath of a disaster the distribution of ratings has shifted toward the left, i.e. it has worsened. In particular, there is a much lower number of suppliers in ratings 7 to 9. [7] At the same time, there are slightly more buyers in some of the bottom categories (1 to 4). However, we find that natural disasters are associated with a lower number of unrated firms

[7]The negative predicted number of buyers in the 8^{th} bin is caused by the concentration of the negative effects of disasters on the suppliers with many buyers. Because of this, the average effect exceeds the average number of buyers in this category.

Figure 9: Effect of Natural Disasters on Buyer Quality after 2 Years



NOTE: These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 5. We include here supplier-time and region-sector-time fixed effects. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue brackets. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2008 and 2019, we consider only the largest one. The outcome variable is the number of buyers each supplier has in each rating category. We plot the sample distribution of ratings in red and its counterfactual distribution in blue.

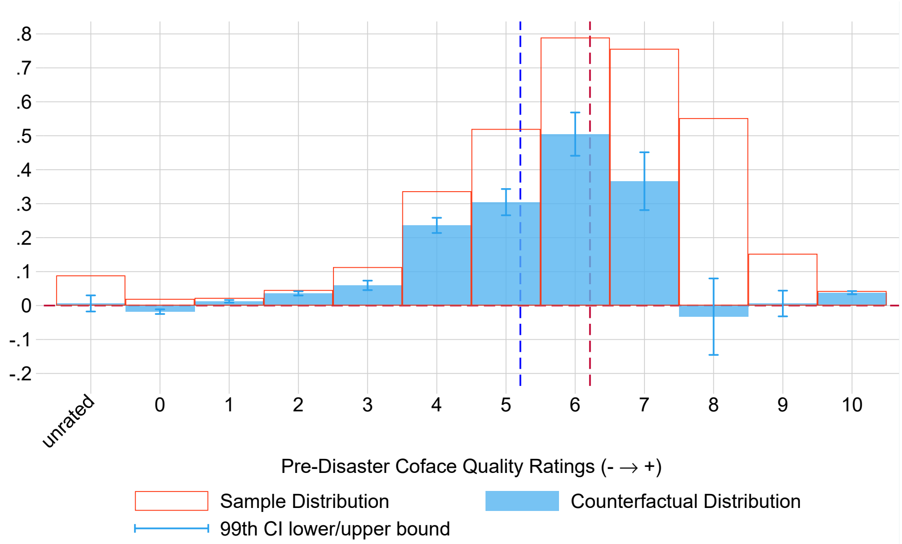
and firms rated 0. This overall effect on the distribution is a combination of "treatment effect" i.e. buyers are being downgraded or "composition effect" i.e. good buyers disappears from the suppliers network.

In Figure 10, we present the same analysis as in Figure 9, but this time we freeze each buyer's rating at the time of the disaster and then count each month the number of buyers still active from each prior category. We compute this variable such that: $T^r_{j,f,t} = \sum \mathbf{1}(EXPO_{j,b,f,t} > 0 \cup R_{b,k} = r)$ with k the month of the event. We see that the drop affects more buyers which were highly-rated at the time of the event (ratings from 7 to 9 with 8 being the most impacted). The most fragile firms are not the most affected ones.

3.3 The role of supplier heterogeneity

In this section we investigate the heterogeneity in the ability of suppliers to adjust to natural disasters abroad. Factors such as a geographically diversified client base, financial constraints

Figure 10: Effect of Natural Disasters on the ex-ante Distribution of Buyer Quality after 2 years



NOTE: These figures present estimates of the counter-factual distribution of buyer quality after a natural disaster event from estimating Equation 5. We include here supplier-time and region-sector-time fixed effects. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue brackets. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2008 and 2019, we consider only the largest one. The outcome variable is the number of buyers each supplier has in each rating category taken at the time of the event. We plot the sample distribution of ratings in red and its counterfactual distribution in blue.

or the sunk cost associated with the establishment of a relationship are likely to affect the choice to pivot toward unaffected destinations or maintain relationships with buyers in the affected destination.

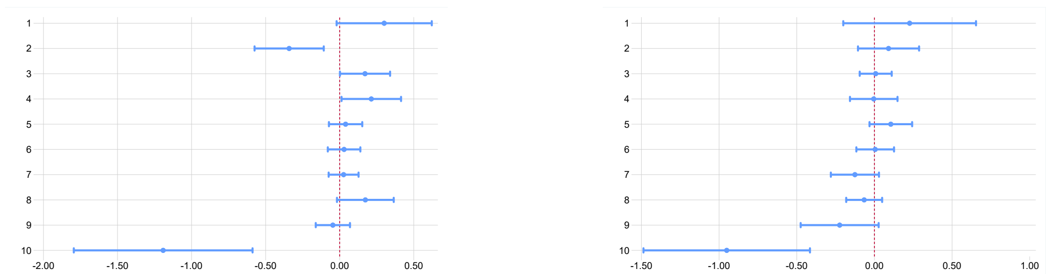
3.3.1 Larger firms are more sensitive to natural disasters

We start by looking at the role played by the overall size of the supplier's customer base in its sensitivity to country-specific shocks. Firms with a large client base are much less reliant on the relationships with their buyers in the affected destination. Compared to small firms, we expect large suppliers to loose more buyers in destinations affected by natural disasters relative to unaffected destinations. We use the same estimator as before but we split the sample along the deciles of the distribution of supplier size and repeat the estimation procedure for each bin of size. We show the results two years after the disaster in Figure 11. We measure size with either the initial total number of buyers (panel 11a) or the initial total trade credit exposure worldwide (panel 11b). In both cases we use the size at the time we first observe the supplier in our sample.

We find that the decline in number of buyers is almost entirely explained by the outcome of suppliers at the very top of the distribution of size. Suppliers above the last decile of the number of relationship worldwide loose 1.2 buyers on average 2 years after the disaster. Meanwhile suppliers below the 9th decile experiences much more modest changes. When using the worldwide trade credit exposure of the firm, we find similar results. Suppliers above the top decile loose 0.95 buyers and suppliers between the 8th and 9th decile loose 0.22 buyers, but slightly non-significant. Suppliers below the 8th decile do not exhibit any meaningful decline in buyers following a disaster.

Figure 11: Effect of Natural Disasters conditional on the supplier size (k=2)

(a) By number of buyers worldwide　　**(b)** By trade credit exposure worldwide



NOTE: Coefficients and 99% confidence interval are reported for two years after the disaster using the De Chaisemartin and D'Haultfoeuille (2020) estimator on sub-populations that includes exporter-buyer pairs where the exporter belongs to the bin of interest. We include here supplier-time and sector-region-time fixed effects.

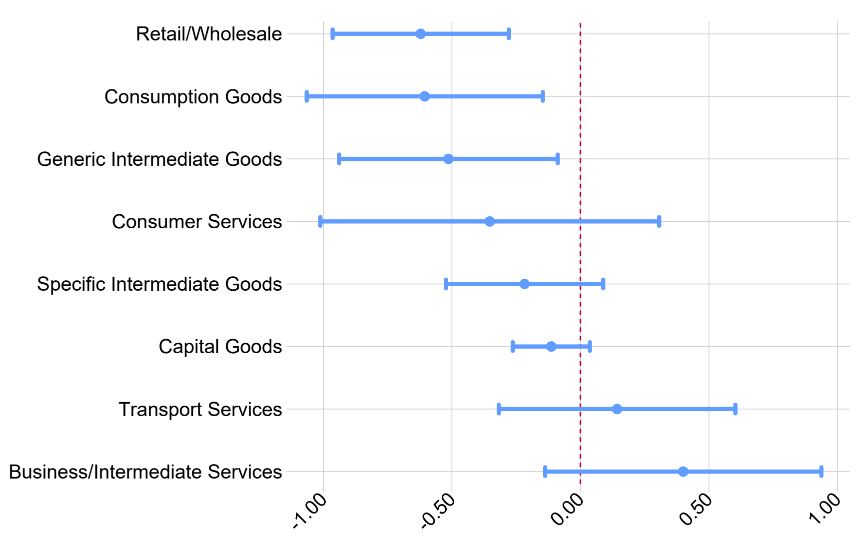
3.3.2 Firms with highly specific output loose less buyers than firms with lower specificity.

We now focus on the heterogeneity in the response to natural disasters based on the type of goods or services sold by the French exporters. As highlighted by Antràs (2020), fixed costs associated with establishing trade linkages are central to explaining the short and medium-term response of Global Value Chains to shocks. They can be of three types: first, the cost associated with information gathering on the targeted market, then, the relational capital to ensure contractual security under incomplete contract enforcement, and, finally, the cost associated with the development of physical assets specific to the buyer-supplier relationship. The more specific a good or service traded between the two firms, the higher the sunk cost. Therefore, the higher the losses associated with the death of the partnership for both parties and the lower the benefits to switch towards other partners. Such effect is expected to be even stronger for trade credit relationships that are typically associated with longer-term trade, as described by Garcia-Appendini and Montoriol-Garriga (2020). Therefore, the specificity of the good or service exchanged will weigh in suppliers' and buyers' decision to end the partnership. We would expect the trade response to natural disasters to be muted for highly specific goods and services, while much greater for non-specific products.

To explore this mechanism, we construct a measure of product specificity using as proxy the sub-sector of the French exporters. We use the four-digit NACE classification and match it with the BEC classification to establish eight types of product categories: capital goods, consumption goods, generic intermediate goods, specific intermediate goods, retail and wholesale, consumer services, business services and transport services.[8] We conduct the same analysis as before using the De Chaisemartin and D'Haultfoeuille (2020) estimator on sample restricted to exporters belonging to each of the above category. Figure 12 synthesizes the heterogeneity in response by category after two years. As expected, the response observed in aggregate is driven by retail and wholesale, consumption goods, and generic intermediate goods, while it is muted for capital goods, specific intermediate goods and consumer and business services. Partnerships around the latter types involve greater sunk costs. Our interpretation of this result is that suppliers and buyers of such specific products tend to protect their relationship to avoid greater losses and save this initial investment.

[8] See appendix E for full description of each category.

Figure 12: Effect of Natural Disasters conditional on supplier output specificity (k=2)

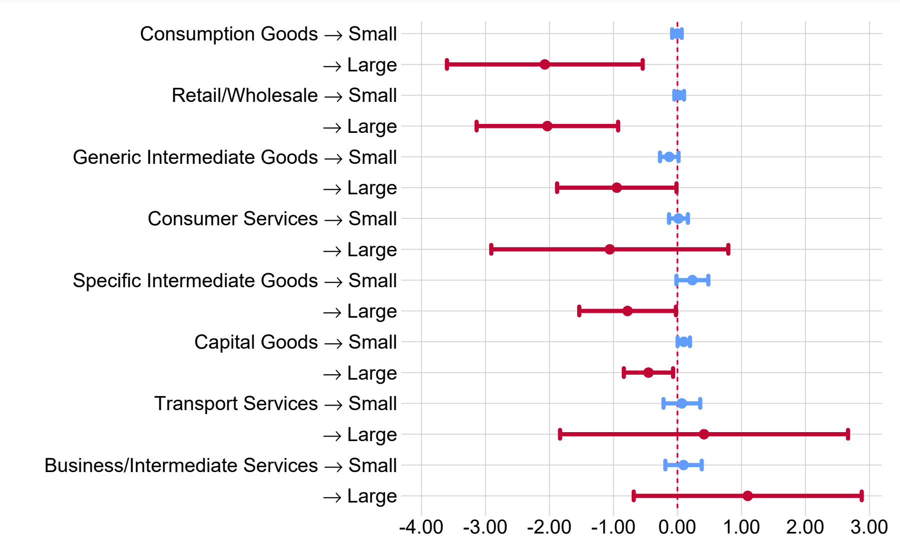


NOTE: Coefficients and 99% confidence interval are reported for two years after the disaster using the De Chaisemartin and D'Haultfoeuille (2020) estimator on sub-populations that includes exporter-buyer pairs where exporters belong to the category of interest. Firms are sorted into categories based on the end-use classification (BEC5 nomenclature) of their sector (NACE 4-digit nomenclature). We include here supplier-time and region-sector-time fixed effects.

3.3.3 For a given level of specificity, larger suppliers exhibit greater reductions in the number of buyers

We now investigate whether the effect of size persists within categories of specificity. We repeat the same estimation procedure as before but we allow the estimated coefficient to vary both by product specificity and size. The specificity categories are unchanged but for simplicity we sort firms within each category into only 2 bins of size. We use the 9^{th} decile of the distribution of the worldwide number of buyers as a cut-off. We report the results in Figure 13. We note two facts. First, within each category, the elasticity of response of large firms dwarfs that of small firms. Second, among large suppliers the sorting by sensitivity to natural disasters follows the same pattern identified above. Firms operating in sectors that produce non specific output experience a larger drop in number of buyers in the affected destinations. The largest firms in retail/wholesale loose 2.0 buyers two years after the disaster whereas large firms producing specific intermediate goods loose 0.77 buyers and those selling intermediate services are not significantly affected.

Figure 13: Effect of Natural Disasters conditional on supplier output specificity and size (k=2)



NOTE: Coefficients and 99% confidence interval are reported for two years after the disaster using the De Chaisemartin and D'Haultfoeuille (2020) estimator on sub-populations that includes exporter-buyer pairs where exporters belong to the category of interest. Firms are sorted into categories based on a combination of the end-use classification (BEC5 nomenclature) of their sector (NACE 4-digit nomenclature) and their initial size measured in total number of buyers worldwide. Firms below (above) the 9th decile are assigned to the "small (large)" category. We include here a supplier-time and region-sector-time fixed effects.

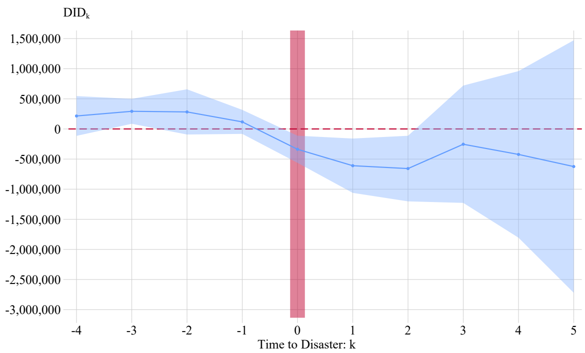
3.4 Net Supplier Effect: A Restructuring of the Network

We've established that natural disasters decrease trade credit flows towards affected locations while creating a noisy and limited response in trade flows. We now investigate whether this translates into global effects at the firm level. Suppliers might be able to divert partnerships toward unaffected destinations. In this section, we compare the dynamics of trade credit flows and exports for suppliers that suffered from a disaster in one of their export markets with suppliers that did not. We consider that suppliers are affected by a natural disaster if one of their export market is hit by a natural disaster as defined in Section 2 and if that export market made up more than 10% of the supplier total trade credit exposure. For suppliers that suffered multiple events, we keep the largest one only. We once again use the De Chaisemartin and D'Haultfoeuille

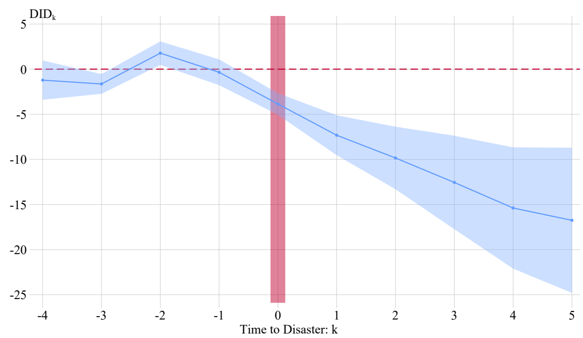
(2020) estimator. In our baseline specification, we introduce a time fixed-effect. We present the results in Figure 14.

Figure 14: Long Run Effects of Natural Disasters on Supplier-level Trade

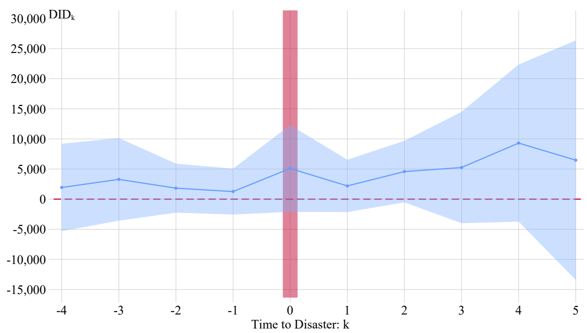
(a) Trade Credit (Euros)



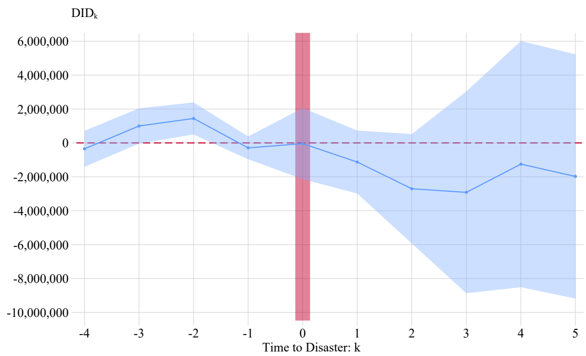
(b) Number of Buyers



(c) Trade Credit per Buyer (Euros)



(d) Exports (Euros)



NOTE: These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 5. 99% error bands, computed with robust standard errors clustered at the sector level, are displayed as blue lines. We include time fixed effects. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2008 and 2019, we consider only the largest one. For suppliers with multiple affected destinations, we consider only the largest one. In Panel 14a, the outcome variable is the total value of trade credit. In Panel 14b, the outcome variable is the number of trade credit partners. In Panel 14d, the outcome variable is total value of exports. See Appendix D for the details on the computations of those variables.

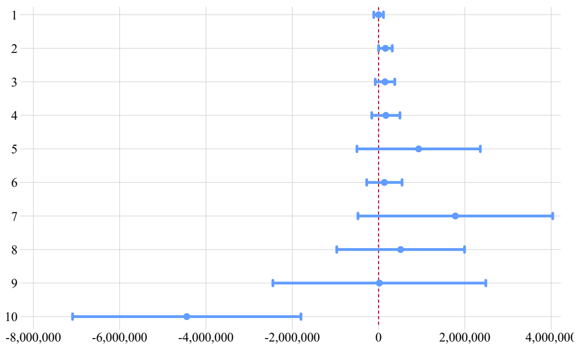
We highlight two key results. First, trade credit exposure experience only a temporary drop while the number of buyers under trade credit terms decline persistently, respectively by 646,941 EUR (panel 14a, 10.9% of the average exposure per supplier in the sample) and 7.8 buyers (panel 14b, 16.7% of the average number of buyers per supplier in the sample) after two years. [9] After 5 year, trade credit exposure is almost back at its pre-disaster level while the number of buyers under trade credit terms has fallen by 16.7 buyers. This means that suppliers do not compensate globally for the buyers they lost in affected destinations. The difference between amount of trade credit and number of buyers is probably related to a small but noisy increase in the average trade credit per buyer in unaffected destination as visible on panel 14c. Second, exports again experience a small and noisy drop (panel 14d). It is worth noting that they follow quite closely the pattern of trade credit sales. We interpret this such that, following a disaster, suppliers rearrange their network of buyers globally without creating new trade credit partnerships.

We now investigate whether this effect is stronger for suppliers with a larger partner base globally. Intuitively, firms with many buyers in unaffected destinations should find it easier to compensate for the losses in the affected destinations. Figure 15a and Figure 15b show that while the largest suppliers are the ones experiencing most of the effect in trade credit exposure, they do not display a significant response in the amount they export (Figure 15c). Once again, the response of exports is noisy and displays a strong heterogeneity. The effect of disasters is only significant on the amount of trade credit and number of buyers for suppliers belonging to the top decile. This means that large multinationals are able to restructure their trade network by either deepening or widening their buyer base in other destinations under alternate financing terms (i.e. without using trade credits). This likely reflects their stronger bargaining power that allow them to set the term of the trade and switch buyers at a lower cost.

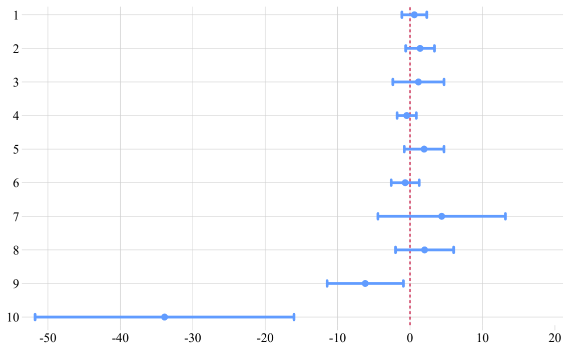
[9]Because of the differences in the event definition, the estimates are not directly comparable to the destination level results in Section 3.1

Figure 15: Effects of Natural Disasters after 2 years conditional on Supplier Size

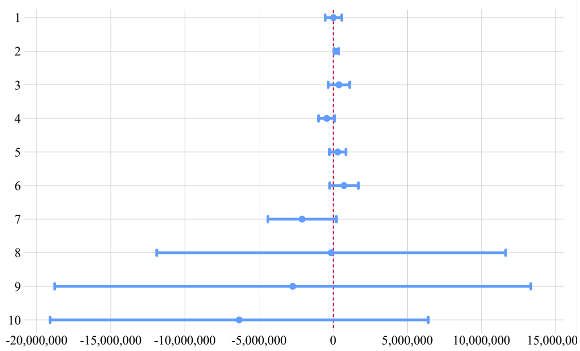
(a) Trade Credit (Euros)



(b) Number of Buyers



(c) Exports (Euros)



NOTE: These figures present estimates of the coefficient $DID_{k=2}$ associated with natural disaster events from estimating Equation 5. 99% error bands, computed with robust standard errors clustered at the sector level, are displayed as blue lines. We include time fixed effects. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2008 and 2018, we consider only the largest one. For suppliers with multiple events, we consider only the largest one. In Panel 15a, the outcome variable is the total value of trade credit. In Panel 15b, the outcome variable is the number of trade credit partners. In Panel 15c, the outcome variable is total value of exports. See Appendix D for the details on the computations of those variables.

4 Robustness

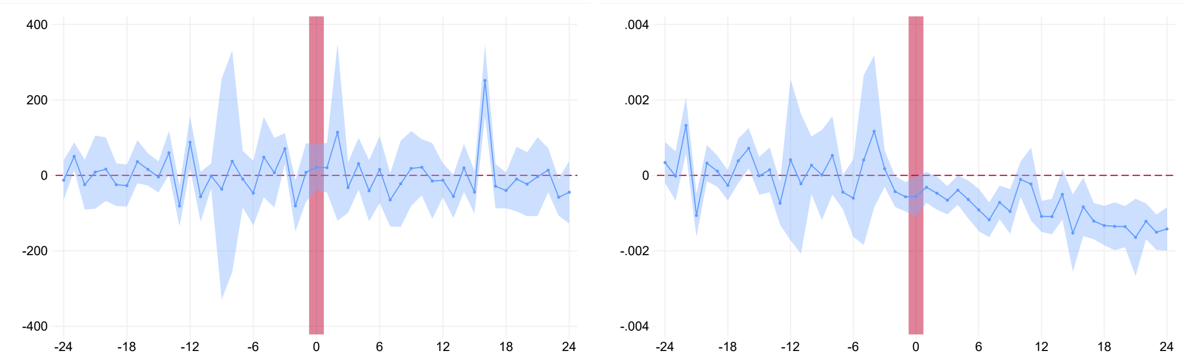
4.1 The effect is not explained by buyers defaulting on their trade credit

To further sketch out the channel generating this fall in quality on the buyer side, we now look at the effect of natural disasters on the occurrence of defaults. Here default include both temporary delays in payments as well as full defaults due to the buyer's insolvency. If buyers default on their trade credit, it would likely severe their relationships with their suppliers. We find no evidence that natural disasters increase the rate at which clients in affected countries default on their trade credit. We even find a small negative effect on the number of defaults. This could potentially be explained by increasing scrutiny on the supplier or the insurer side, given the lower quality of buyers after the disaster. When focusing on defaults due to insolvency, we do not see any significant effect either. Thus, the fall in buyers' quality cannot be explained by the death of buyers.

Figure 16: Effect on Default

(a) Amount of Payment Defaults

(b) Number of Payment Defaults



NOTE: These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 4. We include here a supplier-time and region-sector-time fixed effect. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue lines. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2008 and 2019, we consider only the largest one. In Panel 16a, the outcome variable is the amount of trade credit that buyers in the affected destination default on. In Panel 16b, the outcome variable is the number of defaults. See Appendix D for the details on the computations of those variables.

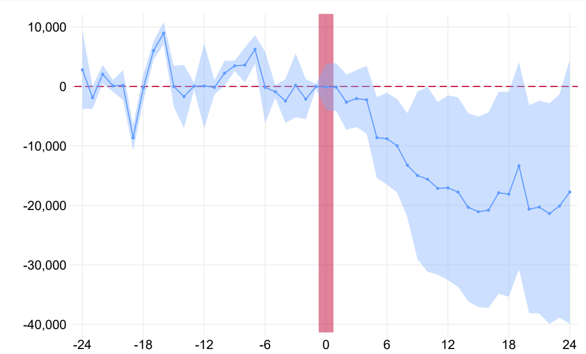
4.2 The effect is not explained by credit insurance rationing

The decline in trade credit to the affected destination could be caused by trade credit insurance rationing. The credit insurer could decide to lower the amount of issued insurance around the time of a disaster. To rule out this mechanism, we use the information on the amount of insurance requested by the supplier and compare it to the amount effectively granted by the insurer Coface. In Figure 17a, we show that the effect of natural disaster on the amount requested follows very closely the effect on the amount granted. We also estimate the effect on the ratio between amount requested and granted (Figure 17b). We find no significant effect.

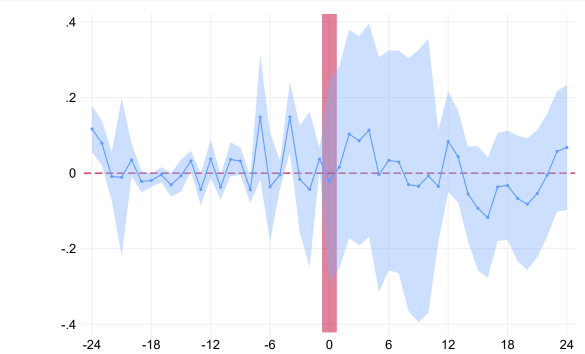
This indicates that the effect reflects a change in demand by the supplier rather than a change in supply by the insurer.

Figure 17: Supplier vs. Insurer Effect

(a) Effect on Requested Amount



(b) Effect on Obtained/Requested Ratio

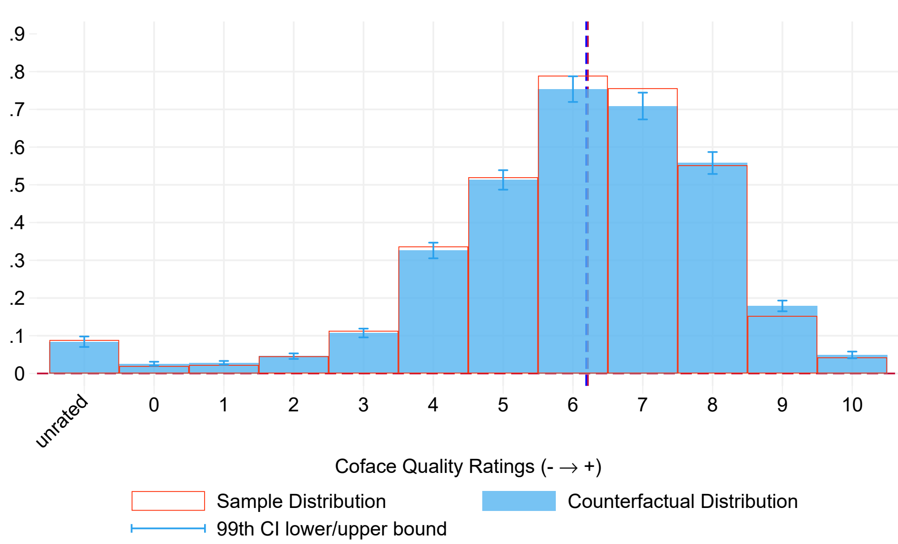


NOTE: These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 5. We include supplier-time and region-sector-time fixed effects. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue lines. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2008 and 2019, we consider only the largest one. The outcome variables are: in Panel 17a the requested amount of trade credit guarantee requested by the supplier and in Panel 17b the ratio of obtained trade credit guarantee over requested. See Appendix D for the details on the computations of all LHS variables.

4.3 Absence of anticipatory effects per ratings category

A potential threat to our identification strategy is that low quality buyers were already experiencing some form of decline prior to the disaster and would have exited the network regardless of the disaster. To investigate this, we repeat the same exercise as in Section 3.1 by estimating the effect on the number of buyers per supplier in each rating category in the two year prior to the disaster. We find no overall meaningful decrease in buyer quality prior to the disaster. We provide the full dynamic response of each rating category in Figure 27.

Figure 18: Effect of Natural Disasters on Buyer Quality 2 Years prior to the disaster



NOTE: These figures present estimates of the coefficient $DID_{k=-2}$ associated with natural disaster events from estimating Equation 5. We include supplier-time and region-sector-time fixed effects. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue brackets. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2008 and 2019, we consider only the largest one. The outcome variable is the number of buyers each supplier has in each rating category. We plot the sample distribution of ratings in red and its counterfactual distribution in blue.

5 Mechanisms

Our results emphasize the importance of the buyer margin in the adjustment to trade shocks. It matches well with the empirical regularity noted by Bernard and Moxnes (2018). Those results can be easily interpreted within a framework of a model of trade with exporter and importer heterogeneity such as Bernard and Moxnes (2018). Both suppliers and exporters are heterogeneous in terms of productivity. They face both a initial sunk cost to establish the relationship and match with the appropriate partner, as well as an iceberg cost for each transaction. Only firms that are efficient enough can afford to trade with one another. Additionally, some of those costs have to be paid upfront which generates financial frictions. Some firms will be more financially constrained than others. It will depend on their ability to secure loans from banks, access financial markets, the degree of pledgeability of their assets, etc. as shown by Manova (2013). In a standard heterogeneous exporters model, those financial frictions raise the Melitz

(2003) type productivity threshold to participate in international trade. Finally, the relationship sunk cost vary greatly depending on the type of products traded. Some goods or services are produced according to the specific requirements of a limited number of buyers (aviation parts or manufacture design services for instance) whereas some others have wider applicability across industries (office furniture or utilities).

In this framework, natural disasters affect bilateral trade mainly through two channels. Damages to transport infrastructure (roads, ports, airports, etc.) temporary increase the buyer-supplier trade cost. Then, by destroying inventories and means of production, natural disasters also induce a temporary negative shift of the distribution of firms' productivity in the destination country. This generates several interesting implications. A natural disaster induces an increase in trade cost, which raises the required productivity threshold and limits the number firms that can participate in international trade. At the same time, the negative productivity shock limits the number of firms that can clear any given threshold. Overall, it implies a lower number of buyers in the affected destination. This is a feature of our empirical results (Figure 5a).

The implications regarding the quality of the surviving buyers are more ambiguous. An increase in trade cost, all else equal, implies a higher selection effect and therefore a higher quality of the remaining buyers. However, a trade cost shock can also provide an incentive for buyers to search for suppliers in destinations with lower trade cost, i.e. a diversion effect. Firms will be affected differently by this mechanism depending on their ability to pay the required search cost. Finally, a fall in productivity among the potential buyers, all else equal, would lead to a lower quality of remaining buyers, i.e. a treatment effect. The fall in quality could also be related to a 'flight from quality' phenomena, with households substituting towards lower-quality goods in the aftermath of the disaster, as highlighted in the Argentinean case by Burstein et al. (2005) following a large devaluation. Empirically, we observe a decline in quality after a disaster (Figure 9). This decline is driven both by firm ratings being downgraded as well as firms with a good rating leaving the production network of the French supplier (Figure 10). "Marginal firms" with a very low rating do not stop importing at a higher rate after a disaster.

Similarly, we do not find any evidence that firms default at a higher rate (Figure 16). Moreover, we do not find evidence of a ’flight from quality’ given the noisy and not fully significant response in the volume exported nor in the number of products exported towards the affected destination. Thus, empirically, the trade diversion effect and to a lesser extent the treatment effect of natural disasters appear to dominate the selection effect.

The higher sensitivity of large supplier of non specific outputs (Figure 13) in combination with the heterogeneity we observe on the buyer side (Figure 10) is indicative of the importance of the adjustment capacity on each side in the aftermath of a large economic shock. The larger the firm, the greater its capacity to respond to the shock and change its sourcing and targeted markets. For both buyers and suppliers, a larger firm will have more opportunities to divert its sourcing/customer base towards more suitable markets. Additionally, firms operating in sectors that do not require a large sunk-cost to establish new relationships have a lower opportunity cost to forgoing existing relationships.

Financial constraints represent another transmission mechanism. Firms that become financially constrained as a consequence of the disaster will choose to reallocate their limited resources towards their more profitable sources. By affecting the value of collateral a firm can pledge to finance trade, it forces them to reorganize their network of partners. While the impact on exporters’ financial constraint in the source country is deemed to be only temporary following the disaster, importers will be more durably affected given the decrease in productivity in the country and its long term impact on collateral value. The long-run effect we observe in our analysis tend to favor a prevalence of an impact through the importers’ financial constraint. Because of their newly limited resources some buyers are likely to reallocate towards more profitable suppliers. They go through a "forced experimentation" as highlighted by (Porter, 1991) with regards to environmental regulation. Given the amount of information frictions in international trade, many buyers might find a supplier that is good enough and it is not longer optimal for them to re-establish a relationship with the original supplier. This would lead to permanent trade diversion as foreign buyers find new suppliers. This also features in our results: losses after a disaster appear to be permanent (Figure 6).

6 Conclusion

In this paper, we show evidence that natural disasters cause large and permanent disruptions to international buyer-supplier relationships. We find that they generate a restructuring of the supplier's network and little net trade destruction. The overall effect on trade is muted at the supplier level thanks to the reshaping of trade networks towards unaffected countries. Natural disasters impact trade in the affected country mostly through the extensive margin by reducing the number of buyers using trade credit rather than the amount of trade credit exposure per buyers. We find that this decreased exposure is caused by a lower demand for trade credit by the supplier rather than a decrease in the amount of insurance granted by the credit insurer. We do not find any evidence of an increase in the number of defaults on their trade credit by clients. We highlight that the negative effect of natural disasters is concentrated among suppliers with many buyers (above 10) rather than suppliers with few buyers in the affected market. We show that the biggest suppliers and best buyers (proxied by the Coface internal rating system) are the ones with the highest exit rate. Decisions to exit is compounded by the level of specificity in the good or service exchanged. For pairs with suppliers producing more specific goods or services, the response is muted compared with the response for generic products. This last result, in addition to the null net trade effect at the global level, reflect how the response to a disaster is largely dependent on the firms' capacity to switch towards alternate buyers at a low cost.

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APPENDIX

A Definition of events

A.1 Timing baseline event: worst disaster in the country

Figure 19: Timing of selected events

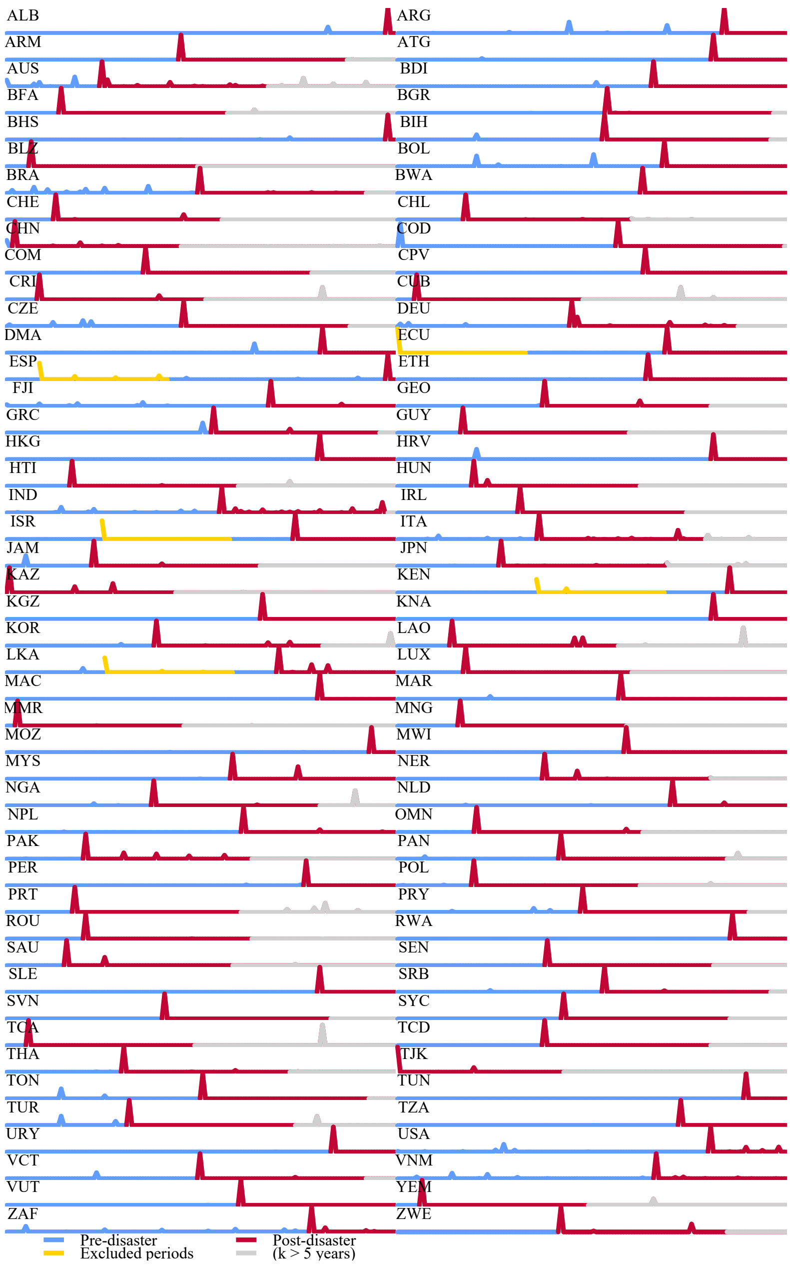
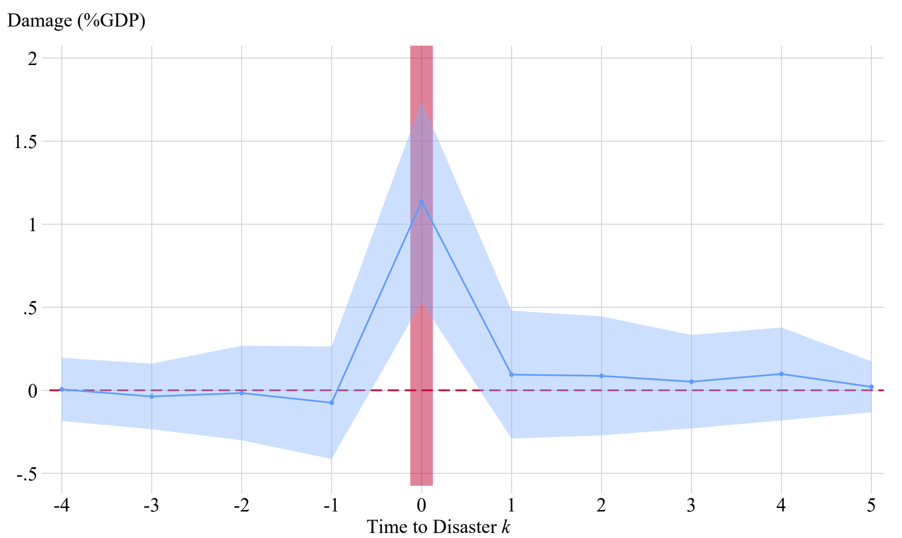


Figure 20: Natural Disasters

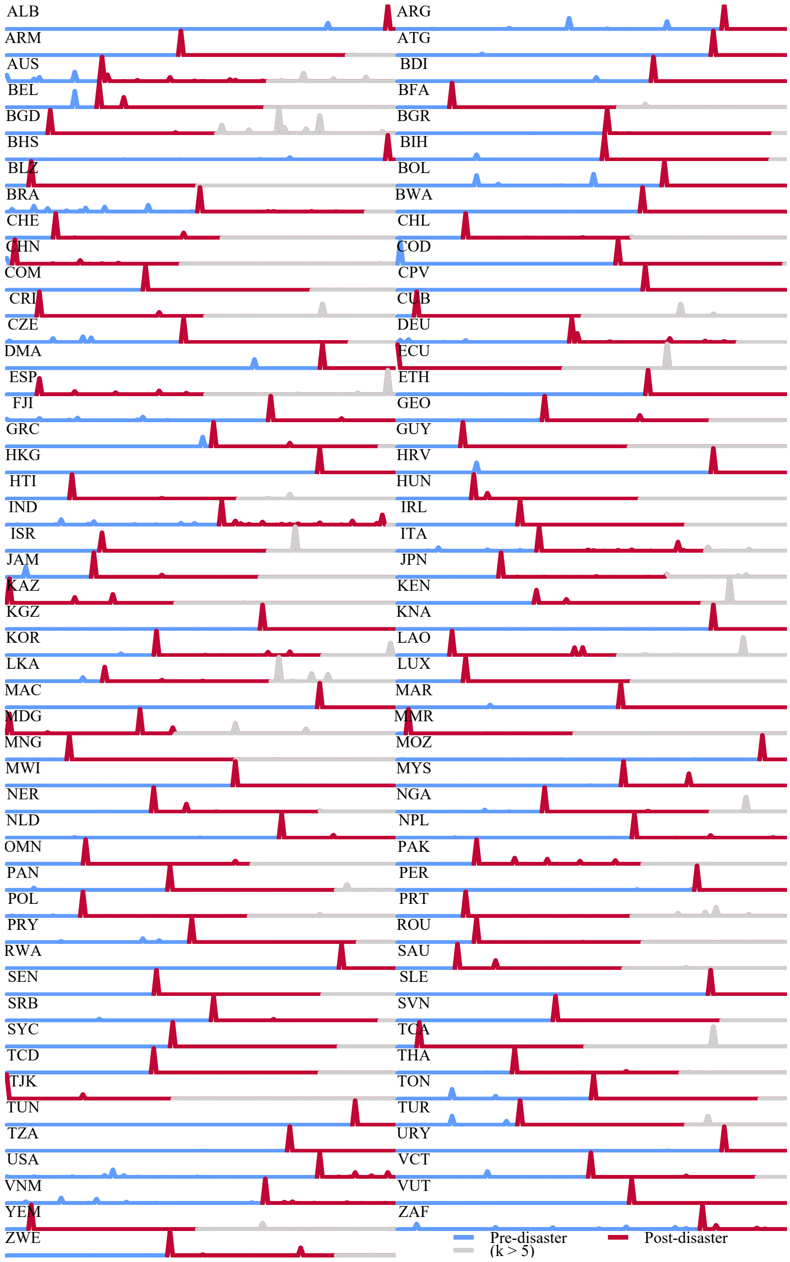


NOTE: These figure presents the response function of estimated damage in percentage of GDP around a natural disaster with our baseline definition. The estimated equation is $D_{j,t} = \sum_k \beta_k + \gamma_j + \gamma_t + \epsilon_{j,t}$

A.2 Timing alternative event: first big disaster in the country

To verify our results, we change our definition to take the first big disaster rather than the worst one in the country. We select this first disaster as the first event causing damages relative to GDP greater than the median in the whole sample, and at least 50% of the intensity of the worst event in the country over the period. We mark as missing any observation polluted with events reaching 50% of the damages caused by this event.

Figure 21: Timing of alternative events

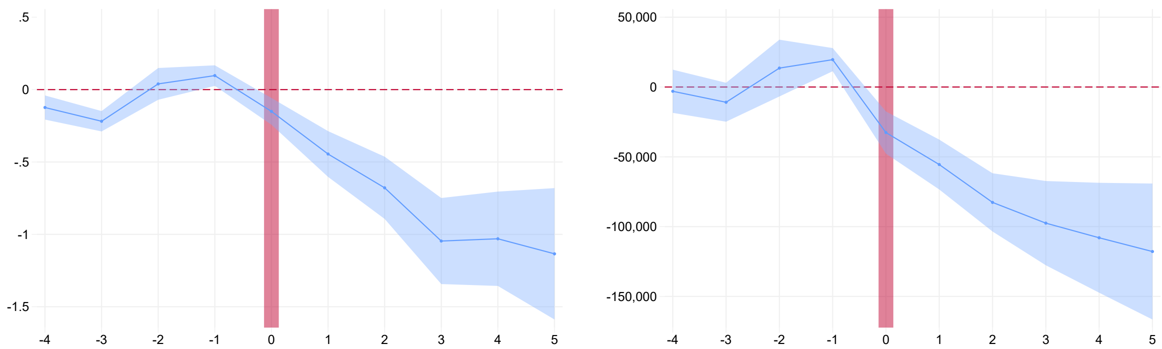


A.3 Main results with first big disasters

Figure 22: Effect of Natural Disasters on the Number of Buyers - First big disaster

(a) Number of buyers

(b) Trade credit amount



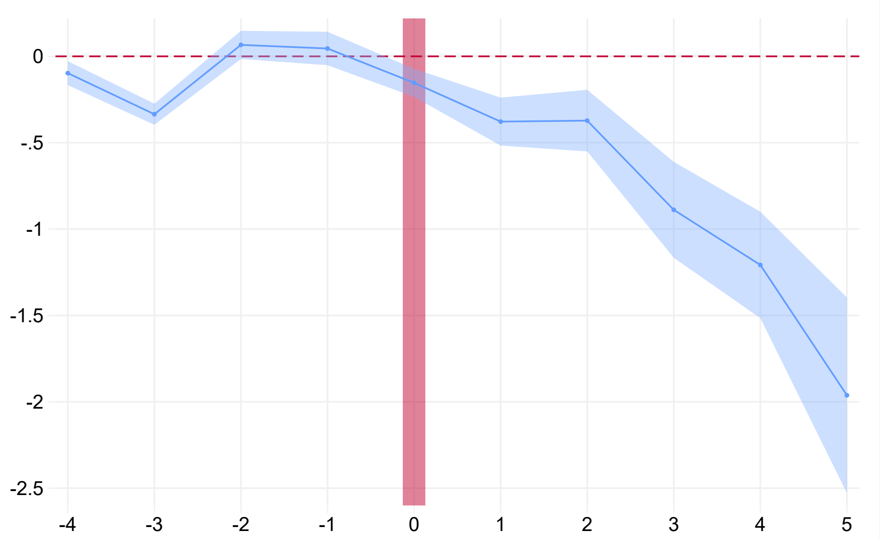
NOTE: These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 5 at the yearly level. We include here a supplier-time and a region-sector-time fixed effects. 99% error bands, computed with robust standard errors clustered at the firm-time level, are displayed as light lines. Events are defined as the first big disaster in the country as shown on the timeline in section A.2. The outcome variable is the number of buyers purchasing from the supplier at credit and the amount of insured trade credit.

A.4 Main results excluding the never treated, first big disaster

A.5 Main results with top quartile disasters

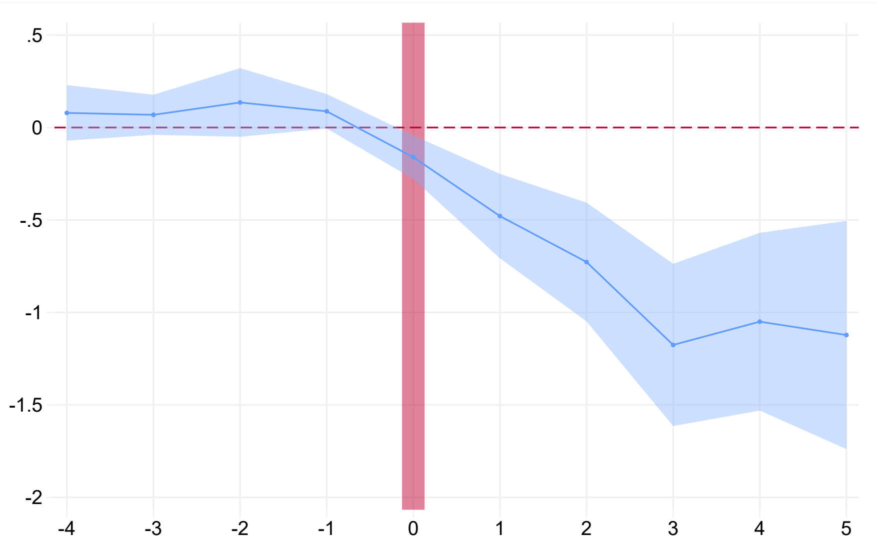
As a last check on our definition of events, we change our definition to take the worst event in the country but change the threshold for the event to be selected. We select a disaster such that it causes damages relative to GDP greater than the third quartile in the whole sample, and such that it is the worst event in the country. We mark as missing any observation polluted with events reaching 50% of the damages caused by this event. We see that the effect is very comparable and even slightly bigger than what we observe with the other definitions presented above.

Figure 23: Effect of Natural Disasters on the Number of Buyers - Excluding never treated



NOTE: These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 5 at the yearly level, excluding the supplier-destinations that are never treated. Events are defined as the first big disaster in the country as shown on the timeline in section A.2. We include here supplier-time and region-sector-time fixed effects. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue lines. The outcome variable is the the number of buyers purchasing from the supplier at credit in each destination country. See Appendix D for the details on the computations of this variable.

Figure 24: Effect of Natural Disasters on the Number of Buyers - Top quartile events



NOTE: These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 5 at the yearly level. We include here supplier-time and region-sector-time fixed effects. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue lines. Events are defined as natural disasters above the third quartile in terms of damage. For countries with multiple disasters in between 2008 and 2019, we consider only the largest one. The outcome variable is the the number of buyers purchasing from the supplier at credit in each destination country. See Appendix D for the details on the computations of this variable.

B Disaster Types

B.1 Definition

Table 4: Disaster Types

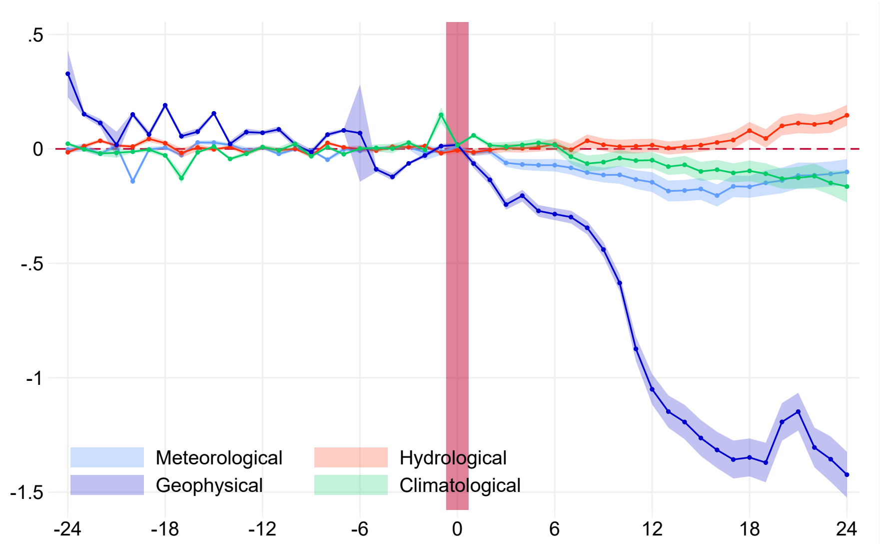
Disaster Group	Disaster Main Type
Geophysical	Earthquake, Mass Movement (dry), Volcanic activity
Meteorological	Extreme Temperature, Fog, Storm
Hydrological	Flood, Landslide, Wave action
Climatological	Drought, Glacial Lake Outburst, Wildfire
Biological	Epidemic, Insect infestation, Animal Accident
Extraterrestrial	Impact, Space weather

This table presents the classification of the main types of natural disasters according to EMDAT classification, see https://www.emdat.be/classification

B.2 Heterogeneity in Types of Disaster

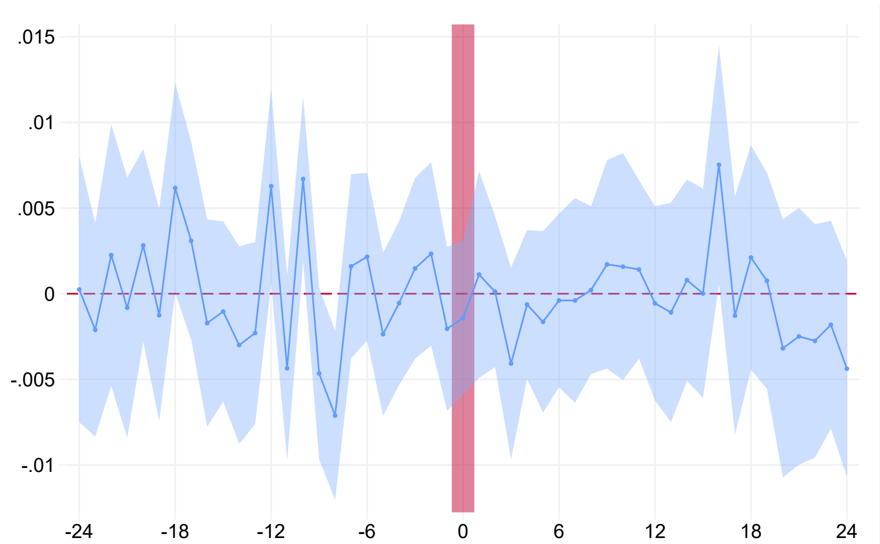
We conduct the same analysis as in section 2 to study the impact of natural disasters on the number of buyers in the affected destination. We use the De Chaisemartin and D'Haultfoeuille (2020) estimator over a set of sub-samples restricted on a specific type of natural disasters. We do this analysis on the four main types of disaster, i.e. meteorological, hydrological, geophysical and climatological. Results are presented in figure 25. We see that most of the fall in the number of buyers in affected destinations is driven by the response to geophysical events and to meteorological events, in line with the amount of damages caused by each type.

Figure 25: Heterogeneity in Types of Disasters



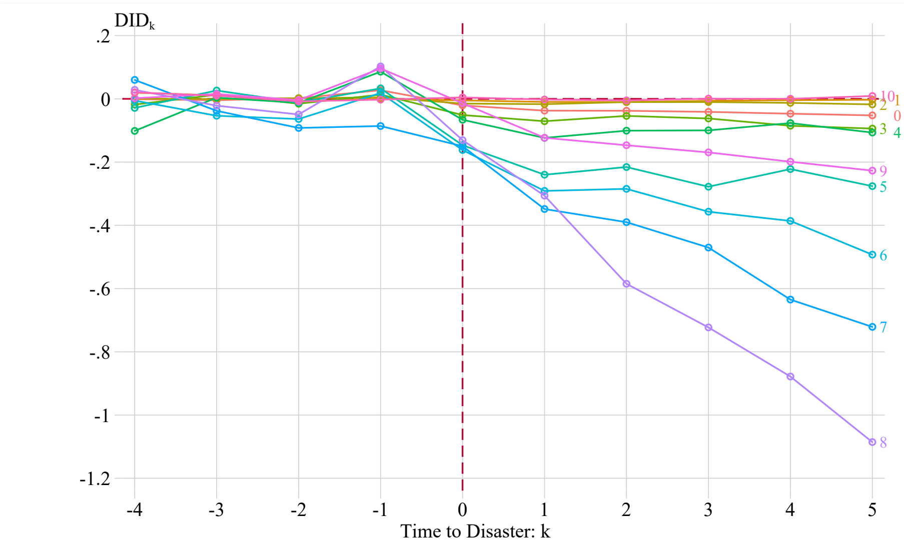
NOTE: These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 5. We include here a supplier-time and a region-sector-time fixed effects. 99% error bands, computed with robust standard errors clustered at the firm-time level, are displayed as light lines.Events are defined according to our main definition described in section 2.1.2. The outcome variable is the number of buyers purchasing from the supplier at credit.

Figure 26: Trade in goods extensive margin



NOTE: These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 5 at the yearly level. We include here a supplier-time and sector-region-time fixed effects. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue lines. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2008 and 2019, we consider only the largest one. The outcome variable is the number of buyers of trade credit insurance for a given supplier in a country. See Appendix D for the details on the computations of all LHS variables.

Figure 27: Effect of Natural Disasters per ex-ante rating category



NOTE: These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 5. Each line represent a different rating category. We include here supplier-time and region-sector-time fixed effects. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue lines. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2008 and 2019, we consider only the largest one. The outcome variable is the amount in euros of trade credit insurance for a given supplier in the affected country. See Appendix D for the details on the computations of this variable.

C Notation

- b indexes buyers
- f indexes suppliers
- j indexes countries
- t indexes periods ie. monthly dates unless otherwise specified.
- n indexes industries
- r indexes large geographical regions according to the World Bank definition. See World Bank WDI.
- k indexes periods (in month unless otherwise specified) relative to a disaster

D Variable Description

- Exposure: Total amount of insured trade credits (referred to as exposure) for each supplier in each buyer country on a monthly basis. (Source: Coface)

$$EXPO_{j,f,t} = \sum_{B} EXPO_{j,b,f,t}$$

- Requested Amount: Total amount requested by the supplier for insurance on trade credit in each buyer country on a monthly basis. (Source: Coface)

$$REQA_{j,f,t} = \sum_{B} REQA_{j,b,f,t}$$

- Total Number of buyers in each buyer country for each supplier. (Source: Coface)

$$TB_{j,f,t} = \sum_{B} \mathbb{1}\{EXPO_{j,b,f,t} > 0\}$$

- Total Number of buyers in each destination country for each supplier for a given rating

$R = r$. (Source: Coface)

$$T^{r}_{j,f,t} = \sum_{B} \mathbf{1}(EXPO_{j,b,f,t} > 0 \cup R_{b,t} = r)$$

- Average length of relations in each buyer country in months at time t: average of the relationship length of with each buyer in the buyer country, starting to count in 2005. (Source: Coface)

$$age_{j,f,t} = \frac{1}{B} \sum_{b} \sum_{t'<t} \mathbb{1}\{EXPO_{j,b,f,t'} > 0\}$$

1

- "Notification of Overdue Account" (NOA) Total Amount: Total amount of defaults on trade credit in each buyer country for each supplier. (Source: Coface)

$$DEF_{j,f,t} = \sum_{B} DEF_{j,b,f,t}$$

- NOA amount protracted defaults: Total amount of protracted defaults (failure to repay not due to buyer's insolvency) in each buyer country for each supplier. (Source: Coface)

$$PDEF_{j,f,t} = \sum_{B} PDEF_{j,b,f,t}$$

- NOA amount insolvencies: Total amount of defaults due to buyers' insolvencies in each buyer country for each supplier. (Source: Coface)

$$INS_{j,f,t} = \sum_{B} INS_{j,b,f,t}$$

Note: Some other causes of default also exists, such as dispute over repayment or the default might not be classified. Thus the sum of protracted defaults and defaults due to insolvencies do not amount to the total.

- NOA nb protracted & NOA nb insolvency : same as amount but with count of defaulters. (Source: Coface)

$$NPDEF_{j,f,t} = \sum_{B} \mathbb{1}\{PDEF_{j,b,f,t} > 0\}$$

- Export Sales: Total amount of sales (in euros) for all products for each supplier in each destination country on a monthly basis. (Source: French Customs)

$$v_{j,f,t} = \sum_{H} v_{j,h,f,t}$$

- Export Quantities: Total amount of sales (in kilograms) for all products for each supplier in each destination country on a monthly basis. (Source: French Customs)

$$q_{j,f,t} = \sum_{H} q_{j,h,f,t}$$

- Number of Products Exported: Total amount of sales (in kilograms) for all products for each supplier in each destination country on a monthly basis. (Source: French Customs)

$$h_{j,f,t} = \sum_{H} \mathbb{1}\{v_{j,h,f,t} > 0\}$$

E End-Use

To classify suppliers depending on their position in global value chains, we rely on the classification by Broad Economic Categories (BEC). We use the 5th edition that incorporates services. We retain 6 broad end-use categories plus transport services and the retail/wholesale sector. classification.

Table 5: End-Use classification

End-Use	NACE 2-digit
Capital Goods	27, 29, 30
Consumption Goods	03, 10, 11, 14, 18, 31, 32, 58
Generic Intermediate Goods	01, 02, 06, 08, 15, 16, 17, 19, 22, 24, 28
Specific Intermediate Goods	13, 20, 21, 23, 25, 26
Retail/Wholesale	45, 46, 47
Consumer Services	35, 38, 55, 56, 79, 85, 87, 90, 94, 95, 96, 99
Business/Intermediate Services	41, 42, 43, 59, 60, 61, 62, 63, 68, 69, 70, 71, 72, 73, 74, 77, 78, 80, 81, 82
Transport Services	49, 50, 51, 52

This table presents the classification of NACE 2-digit sector by type of products.