Trade Networks and Natural Disasters: Diversion, not Destruction

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October 27, 2021

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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 differences-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 strong and permanent negative effects on French suppliers' exports and 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 divert trade toward unaffected destinations, leaving their overall export level to be mostly unaffected. Trade diversion is higher for large multinationals trading more homogeneous products.

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

Keywords: Firm Dynamics; Trade Networks; Natural Disaster.

Acknowledgement: We are grateful for the comments and suggestions of Isabelle Méjean, Yann Bramoullé, Philippe Aghion, Jean-Stéphane Mésonnier and numerous seminar participants at the INSEAD, the Collège de France, the CREST, the Banque de France, the Aix-Marseille School of Economics, the 2021 Young Economist Symposium, the INFER Annual Conference and the AFSE 2021 conference.

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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. 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 with exhaustive disaster data from EM-DAT. We then estimate the causal 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 differences-in-differences identification strategy. We employ the de Chaisemartin and d'Haultfoeuille (2020) estimator and provide an estimate that is robust to heterogeneous treatment effects. Within that framework, we control alternatively for supplier-period shocks and geographical region-sector-period shocks.

We find evidence of large and persistent disruptions to international buyer-supplier relationships. French suppliers decrease their trade credit exposure to affected countries in similar proportion to the observed fall in total exports. After two years, the level of exports has fallen by 5.61% (€11,300). In the same time-frame, trade credit exposure has declined by 11.58% (€29,600). 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 7.22% (0.18 buyers) after 24 months. This fall in the number of buyers is persistent, as we find a decrease of about 0.94 after four 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 that are typically larger firms. Moreover, disasters are not followed by a rise in insolvencies in afflicted destinations. The greater sensitivity of larger firms to natural disaster also appears on the supplier side. Suppliers above the tenth decile of size (in their initial worldwide number of buyers or exposure) drive most of the observed average effect of natural disasters. At the same time, suppliers with few buyers in the affected country (between 2 and 10) are the ones to experience the greatest losses. Those two results likely reflect a lower opportunity cost for bigger suppliers to switch away from the affected country where they are less established. They have already access to a well-structured network of alternative buyers in other destinations without disbursing additional costs. This result is confirmed by an analysis at the supplier level. Overall, exports by suppliers are mostly unaffected, while the number of buyers under trade credit terms and the amount of trade credits decrease. It is easier for large multinationals with already a wide range of destination countries to divert the extra trade to other destinations. 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 0.8 and 1.80 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 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 2010 and 2020 rather than focusing on a specific event. Second, our data is not restricted to foreign affiliates or publicly traded firms. 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) shows 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 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 US production networks 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 afflicted 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) finds that uncertainty reduces 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

[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, the find that large exporters accounted for a disproportionate share of the losses

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' switching costs to replace those clients. The harder the buyer is to replace, 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) finds 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 might 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. When the supplier intends to get insured for the export market, it has to provide the full set of buyers under trade credit terms on this market. 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 at Coface between 2010 and 2019. Supplier are identified by a French fiscal identifier (siren code). 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 Coface internal rating of each buyer. We also have information on the amount of exposure requested by the supplier to Coface and the amount awarded by Coface. Finally, we also use the number and amount of payment defaults from buyers notified to Coface in each market. The two main types of defaults are 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-period fixed effects in our analysis.

Coface ratings are based on a combination of fiscal data, experts opinions and external ratings. A rating of 0 is the lower 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

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.

[3] Internal Coface documentation.

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 to each NACE 4-digit sector a BEC5 code. We can then group sectors together based on the amount of coordination between the buyer and the seller required 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, the number of firms in Coface database is equal to 16% of those in French custom data. 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.

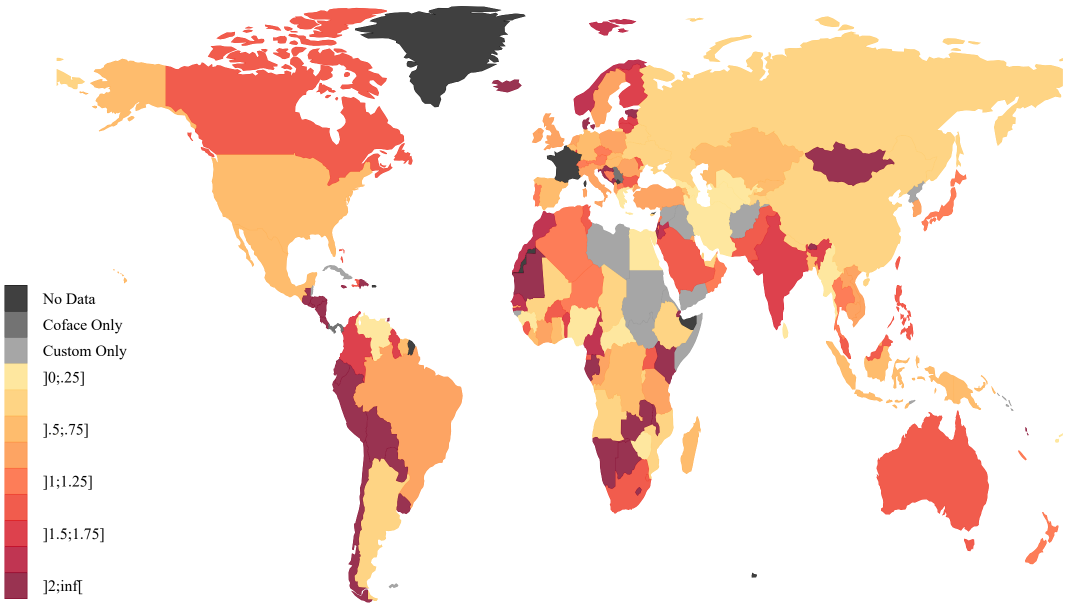
2.1.2 Disaster Data

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,

[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."

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

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.

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 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 $D_{j,t}$ is greater than the median for all disasters and if it is the worst event in this country between 2008 and 2019:

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

Table 2 synthesizes key summary statistics for natural disasters recorded by EM-DAT over the period. We do not record disaster event for 69 countries as the recorded estimated damage falls below the median for all natural disasters. Among the 129 recorded events, the most frequent type is hydrological (55 events). The most destructive type is geophysical (USD Mn. 18,309 on average). The description of the main types of disasters can be found in appendix A.1.

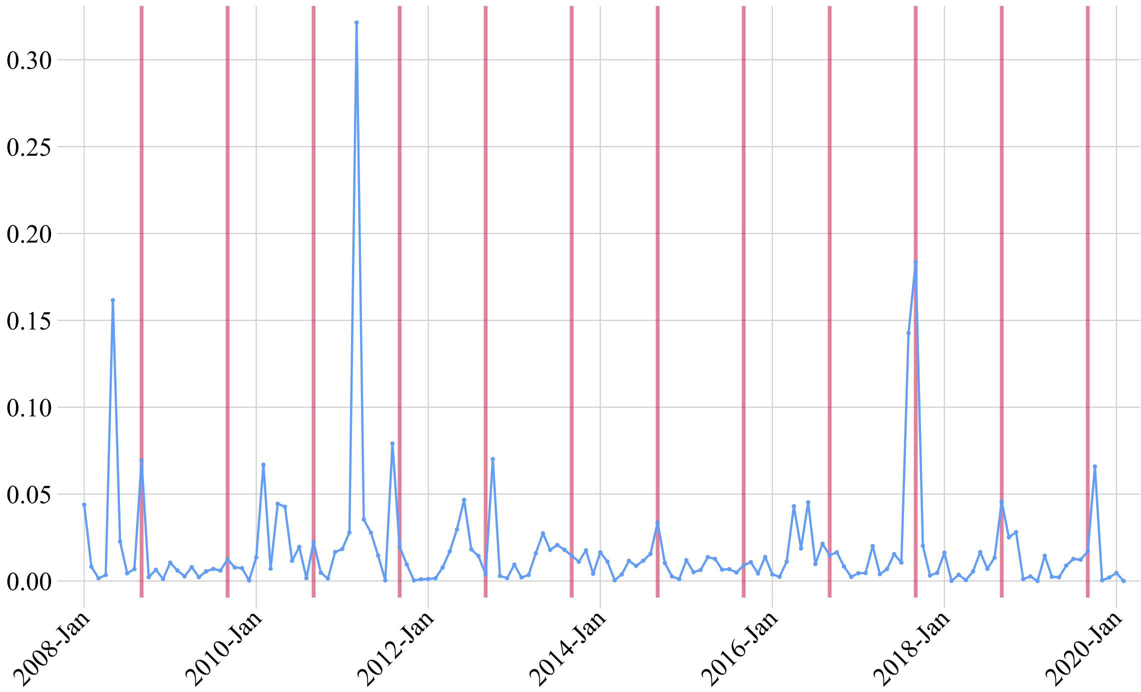
Table 2: Natural Disasters (2008-2019)

	N	Mean	Median	Std.Dev.
All Disaster Types				
Estimated Damage (USD Mn.)	129	5699.96	500.00	22521.43
Estimated Damage (% GDP)	129	7.17	0.69	26.57
Type = Climatological				
Estimated Damage (USD Mn.)	13	1136.52	500.00	1804.07
Estimated Damage (% GDP)	13	1.00	0.71	1.01
Type = Geophysical				
Estimated Damage (USD Mn.)	21	18309.48	740.00	47873.06
Estimated Damage (% GDP)	21	9.94	0.73	26.64
Type = Hydrological				
Estimated Damage (USD Mn.)	55	2332.63	436.58	6064.73
Estimated Damage (% GDP)	55	1.58	0.49	2.84
Type = Meteorological				
Estimated Damage (USD Mn.)	39	5323.74	553.00	18347.10
Estimated Damage (% GDP)	39	15.81	1.24	43.05
Type = Technological				
Estimated Damage (USD Mn.)	1	100.00	100.00	.
Estimated Damage (% GDP)	1	0.03	0.03	.
No Disaster				
Estimated Damage (USD Mn.)	69	2.19	0.00	12.40
Estimated Damage (% GDP)	69	0.00	0.00	0.01

NOTE: The source for the disaster data is EM-DAT. Authors' computations.

Figure 2 represent 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. However damage caused during storm seasons appear to be increasing.

Figure 2: Natural Disasters



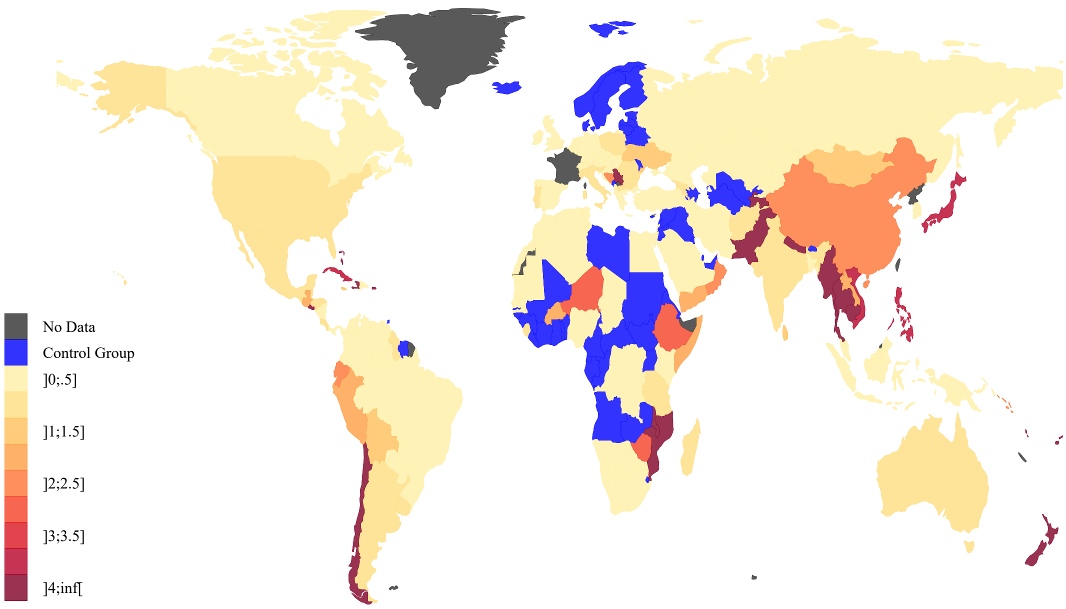
NOTE: These figure presents estimated damage in percentage of GDP caused by natural disasters. The source for the disaster data is EM-DAT. Authors' computations.

Figure 3 shows the geographical distribution of natural disasters events as defined by Equation 2. Countries marked in blue compose our permanent 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 0.69 percent of GDP. Only eight of them caused damages equal to more than 4 percent of GDP.

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. We have 146,833 distinct

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

supplier-destination linkages in 181 countries and 9,615 French suppliers. Of those supplier-destination dyads, 29,537 (37%) are never treated. The rest suffers from a natural disaster at some point during 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. We look at 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). We assume a simple data generating process such as:

$$\Delta Y_{f,j,t} = \gamma_t + \beta \times \texttt{DISASTER}_{j,t} + \epsilon_{f,j,t} \tag{3}$$

Where Y is some variable describing the trade network outcome of supplier f in the destination country j at period t. The change of Y is determined by some time varying components common to certain groups of observations regardless of their treatment status. Those could be the business cycle in the destination country or firm-specific supply shocks.

We rely on a Differences-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 differences-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) Differences-in-Differences estimator absorbs permanent differences between destinations. To account for time varying shocks, we residualize the outcome variables over either region-sector-month or firm-month fixed effects. The former accounts for common shocks across supplier-destination pairs within regions-sectors-months. The identification comes comparing several suppliers operating in the same sector but exporting to different countries within the same region, where at least one will be affected by a disaster. The latter accounts for the suppliers shocks common to all their destinations. This specification limits the sample to supplier present in two or more destinations. Here, identification results from the supplier exporting to at least two different countries, one of which is hit by a disaster at some point. 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. The estimator does not allow for the combination of two fixed effects, so we compare results using each one alternatively.

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 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.

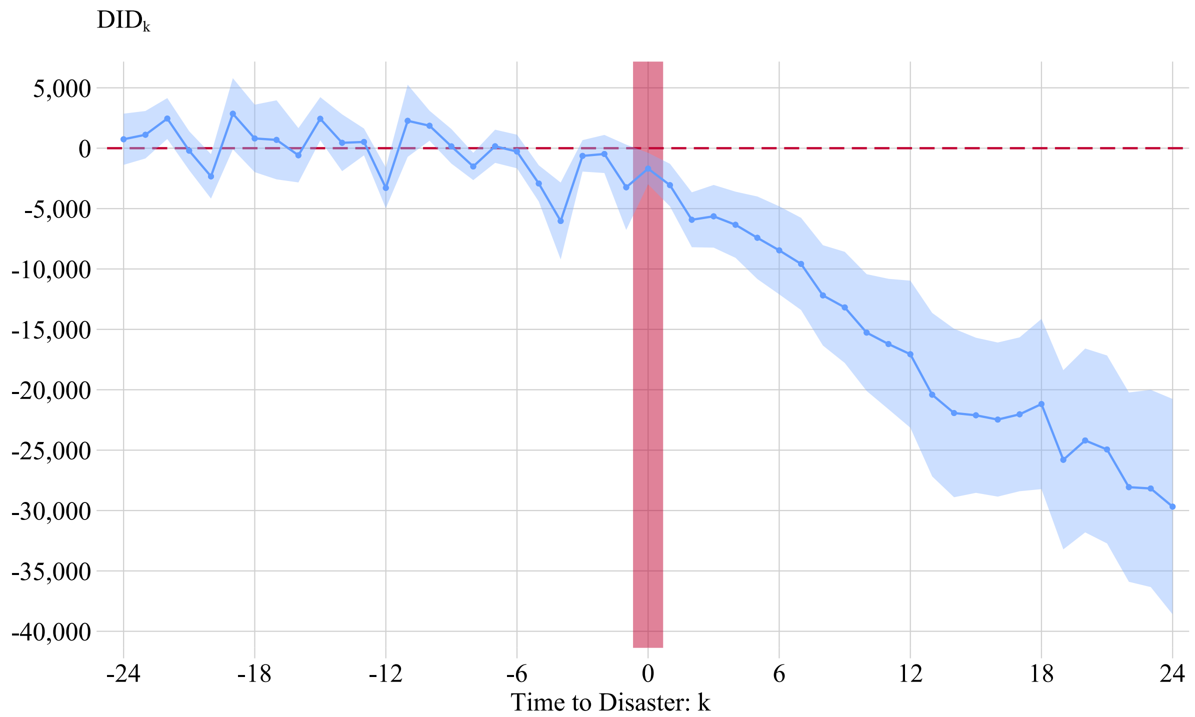
3.1 Main Results

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 €17,000 after 12 months and €29,600 after 24 months. The average trade credit exposure is 256,150 (P50 = 10,000; SD =1,929,330). The total loss after 24 months represents a 6.66% (12 months) and a 11.58% (24 months) decrease in trade credit exposure to the affected destination relative to the sample mean. In appendix B we confirm this decrease in exposure using a two-way fixed effect estimator.

The decline is entirely explained by the "2^{nd} extensive 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 "1^{st} extensive margin" i.e. the existence of a trade credit relationship in the destination country and the "2^{nd} extensive margin" i.e. the number of buyers using trade credit terms in the destination country. To measure the

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 a supplier-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. 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.

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 2^{nd} extensive margin, i.e. the number of clients rather than the exposure per client. The effect increases from about from -0.11 buyers after 12 months to -0.18 buyers after 24 months and is robust to the inclusion of firm-time fixed effects and sector-region-time fixed effects (Figure 5a). The average number of buyers in the sample is 2.49 (P50 = 1; SD = 13.51). This represents a 7.22% decline in the number of buyers using trade credit 24 months after a disaster. Meanwhile, we find no effect on the probability of being present in an affected destination (Figure 5b). We also find no impact on the intensive margin (Figure 5c).

In section A.2 in appendix, we focus on the second extensive margin and the heterogeneity in terms of disasters, following EM-DAT classification. We find that geophysical events, 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 -1.21 buyers following a geophysical event. Meteorological events, also causing large disruptions, tend to cause a smaller response even though negative. For hydrological and climatological events, the small but positive effect should be interpreted in line with the limited damage typically caused by these two types of disaster (see table 2). Such results reflect the heterogeneity in the extent of damages caused by each type of disaster.

Persistence of the effect after five years

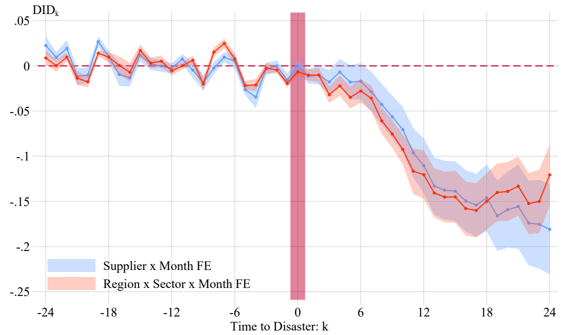
To assess the long run consequences of natural natural, we repeat the same estimation procedure as in Equation 4 and Figure 5a on a sample aggregated at the yearly level. We present those results in Figure 6. We find that the number of buyers in the affected country continues on declining until four years after the natural disaster. The average loss at this horizon is 0.94 buyers per supplier.

The effect is concentrated on suppliers with few buyers in the affected destination

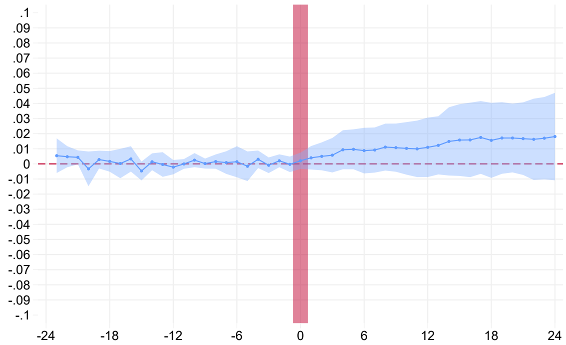
To further isolate the margin through which firms adjust to external shock, we estimate the effect of a natural disaster on the cumulative distribution of buyers per supplier-destination. We've seen that natural disasters has little effect on the probability of having at least 1 buyer in the destination while at the same time it reduces the number of buyers per supplier. We now investigate 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

Figure 5: Extensive and Intensive margin

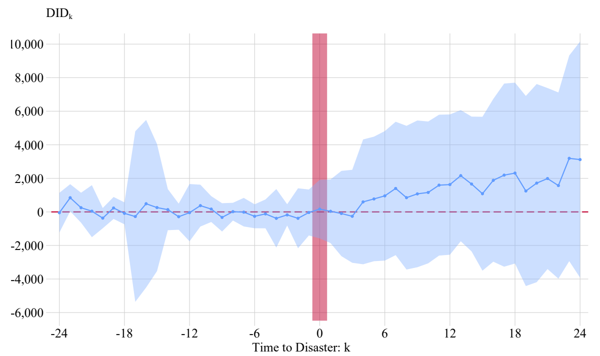
(a) Number of Buyers with Trade Credit



(b) 1st Extensive Margin



(c) Trade Credit / Number of buyers



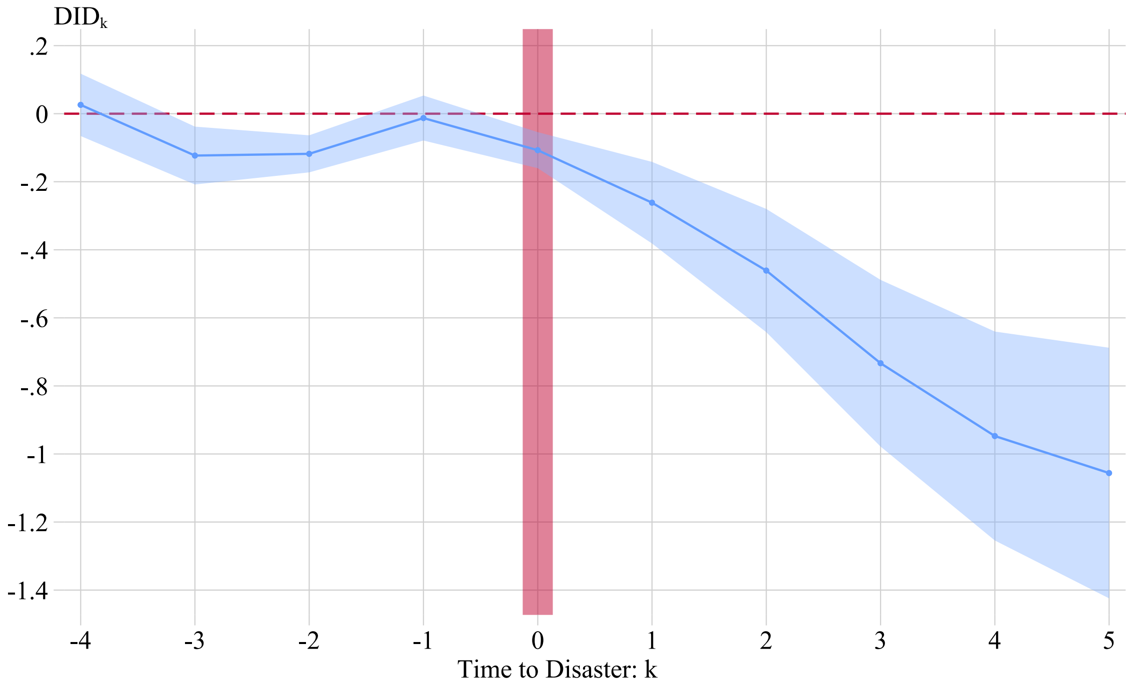
NOTE: These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 5. 99% error bands, computed with robust standard errors clustered at the region-sector level, are displayed as blue lines. Events are defined as natural disasters above the 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 fixed effects (red line) and sector-region-time fixed effects (blue line). 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.

(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 just a few buyers per destination. The effect on the probability of having at least a single buyer is slightly positive (about one percentage point) but not statistically significant. A disaster decreases the probability of having more than two buyers by 1.2 percentage points and more than five buyers by about 0.8 percentage points.

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

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. We include here a supplier-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. 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.

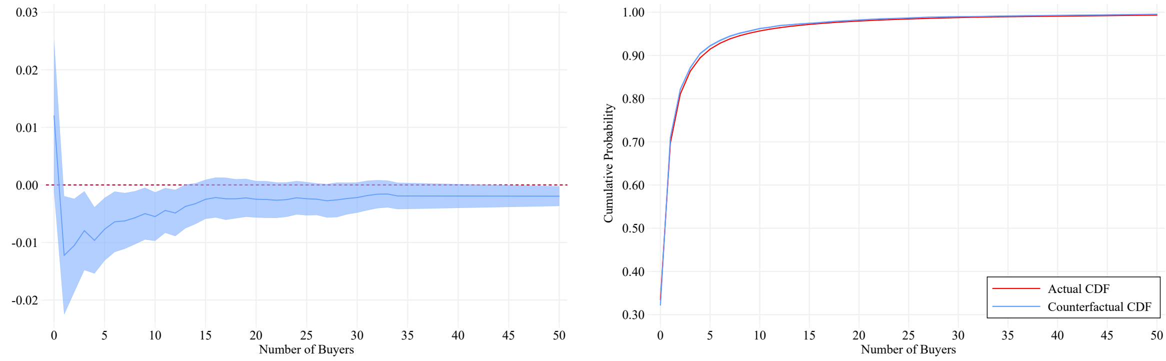
The higher in the distribution, the lower the effect is. This effect stabilize at about minus 0.1 percentage point between the 95^{th} and 99^{th} percentile of the distribution. We show in Figure 7b that it results in a shift of the cumulative distribution towards the left. In other words, the new distribution of buyer-per-supplier includes a lower number of suppliers with a few buyers (but strictly more than 1). Suppliers with a single foothold did not loose it and suppliers with a large local buyer base went mostly but not completely unaffected.

Customs measured trade and natural disasters

One might be worried that our empirical results are an artifact of the trade credit data from Coface and may be absent from more traditional data collected by the French customs. In particular, we cannot fully confirm that the end of a trade credit relationship means the end

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 a 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 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).

of the underlying trade relationship. However, the decrease in the number of buyers using trade credit likely reflects a lower number of domestic firms sourcing from French suppliers. Indeed, according to previous work by Garcia-Marin et al. (2020) firms rarely switch away from trade credit. We investigate this by looking at the effect of natural disasters on the actual supplier level exports as measured in custom data. We keep the same specification as before. The sample contains firms that are present in both French customs and Coface datasets. As a consequence it only extends from 2010 to 2018. We first estimate the effect on the total value in euros exported by French suppliers to their destination. 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 value of the transactions toward the affected destinations decreases by about €11,300 in the two years following a disaster. This effect increases to about minus €18,900 after five years. In panel 8b, we see that the effect on quantities tracks closely the one on values. In fact, panel 8c shows that the effect on unit values while positive, is not statistically significant. Finally, panel 8d indicates that natural disasters leads to a lower number of exported products (-0.15) after five years. We also do not find evidence of an effect on the probability of exporting to a country struck by a natural disaster (not reported here).

We can make three observations from this last set of results. First, the overall pattern of results is similar whether we use the French custom or the Coface database. Natural disasters causes a permanent drop in the intensity of the trade linkages with the affected destination. Second, the effect on the number of products (Figure 8d) are consistent with our results on the decrease in the number of buyer-supplier relationships (Figure 5a) and underlines the importance of the within-country extensive margin in the adjustment to major shocks. Third, the losses measured in trade credit and in export sales are of a similar order of magnitude. After just two years, the level of traded goods has fallen by €11,300 (Figure 8a). This represents a 5.61% decline versus a 11.58% decline in trade credit. This indicates that a large negative shock not only impacts the size of the trusted network of buyers to whom the supplier will extend trade credit. It also impacts the underlying cross-border movement of goods.

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

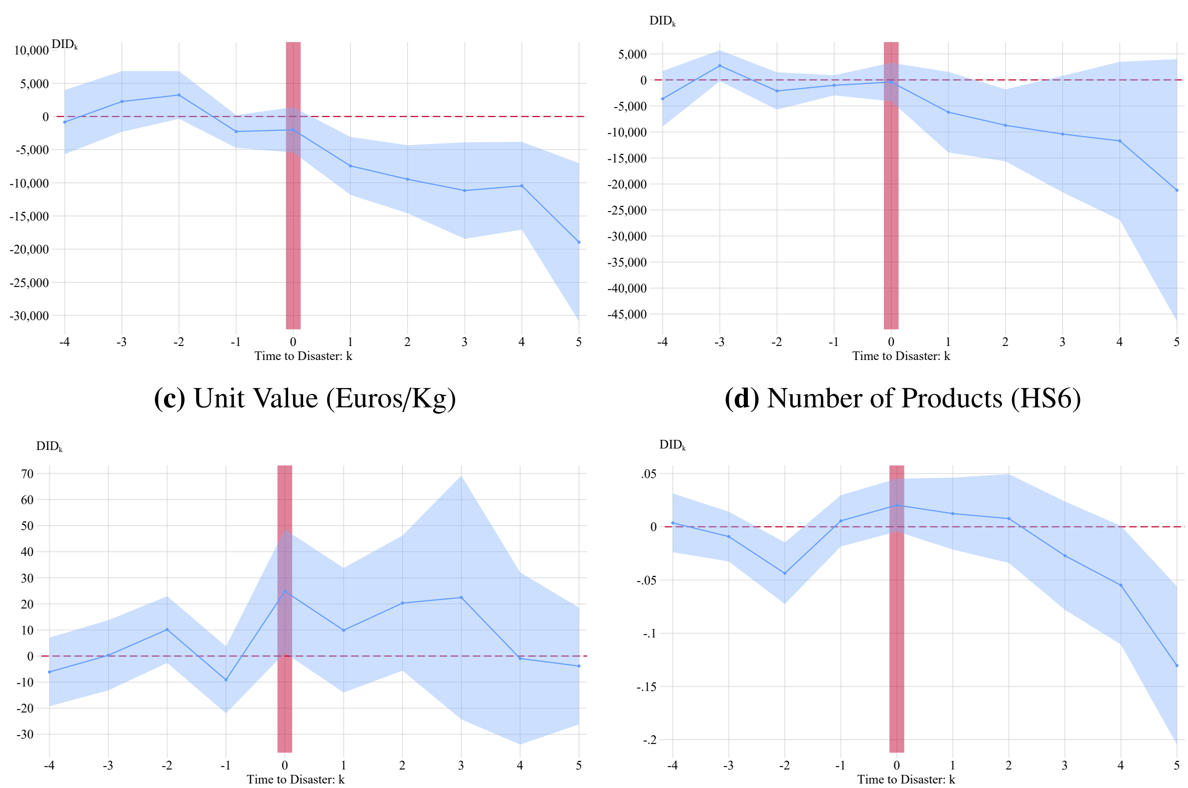
We now focus on the effects of disasters on the quality of the supplier's network of buyers in the destination country. We proxy quality with the Coface internal ratings of buyers.

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 either region-sector-time fixed effect or 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.

We find that in the aftermath of a disaster the distribution of ratings has shifted toward the

Figure 8: Long Run 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)

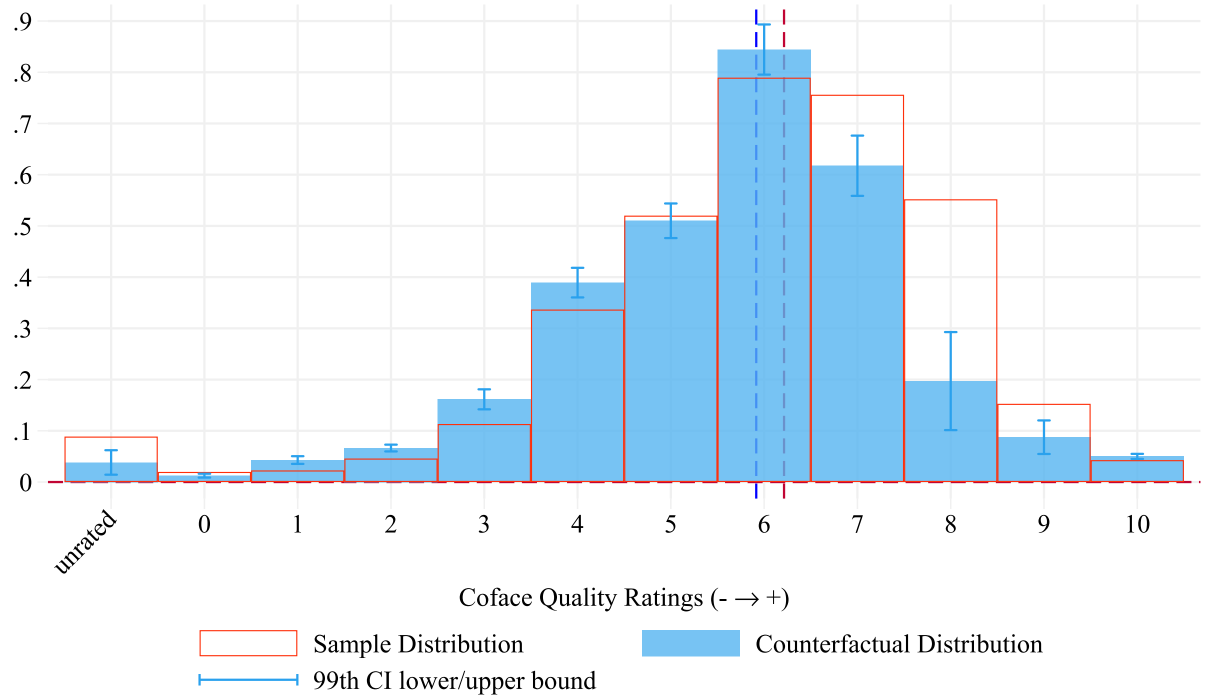


NOTE: These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 5. We include here a supplier-time fixed effect. 99% error bands, computed with robust standard errors clustered at the region-sector level, are displayed as blue lines. Events 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 total value in euros exported by french suppliers to their destination. In Panel 8b, the outcome variable is the quantity exported in kilograms. In Panel 8c, the outcome variable is the unit values (euros per kilogram) of the exports. In Panel 8d, the outcome variable is 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.

left, i.e. it has worsened. In particular, there is a much lower number of suppliers in ratings 7 to 9. 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 and firms rated 0. This overall effect on the distribution can be 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

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



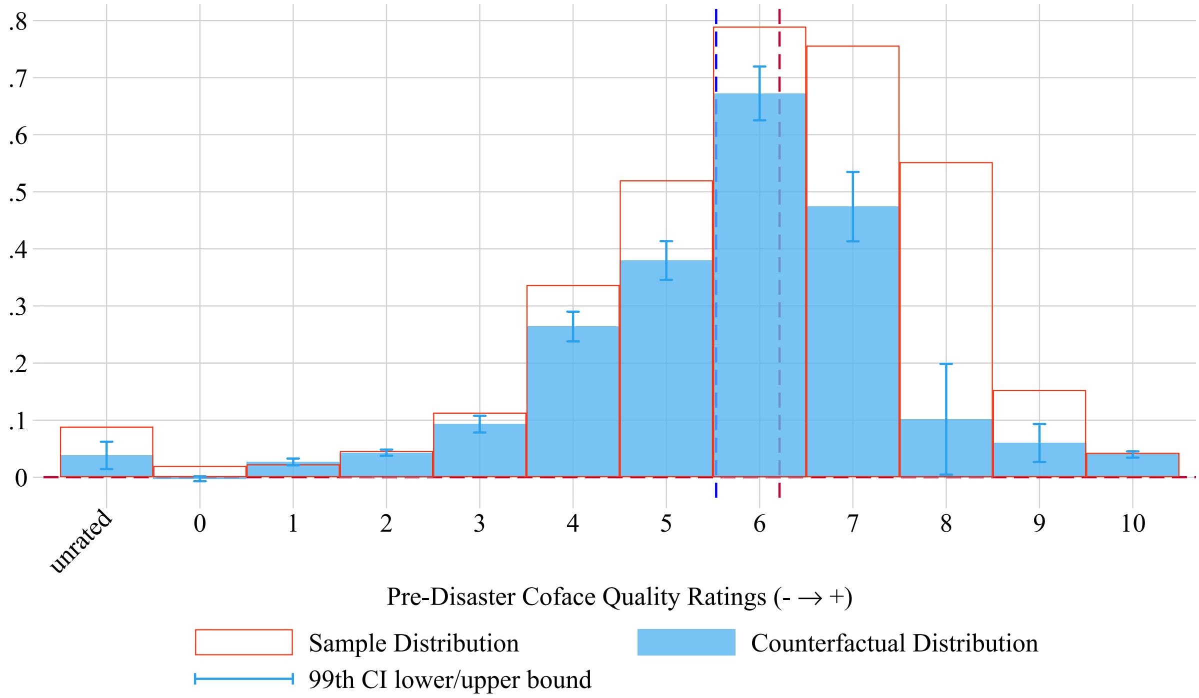
NOTE: These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 5. We include here a region-sector-time fixed effect. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue brackets. Events 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.

active from each prior category. We compute this number doing: $T^r_{j,f,t} = \sum \mathbf{1}(EXPO_{j,b,f,t} > 0 \cup R_{b,k} = r)$ 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

The purpose of this section is to investigate to what extent the ability of some suppliers to adjust matters in their sensitivity to natural disasters abroad. Factors such as a geographically diversified client base, financial constraints or the amount of sunk cost needed to establish a relationship are likely to affect the choice to pivot toward unaffected destinations or maintain relationships with buyers in the affected destination.

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 a region-sector-time fixed effect. 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.

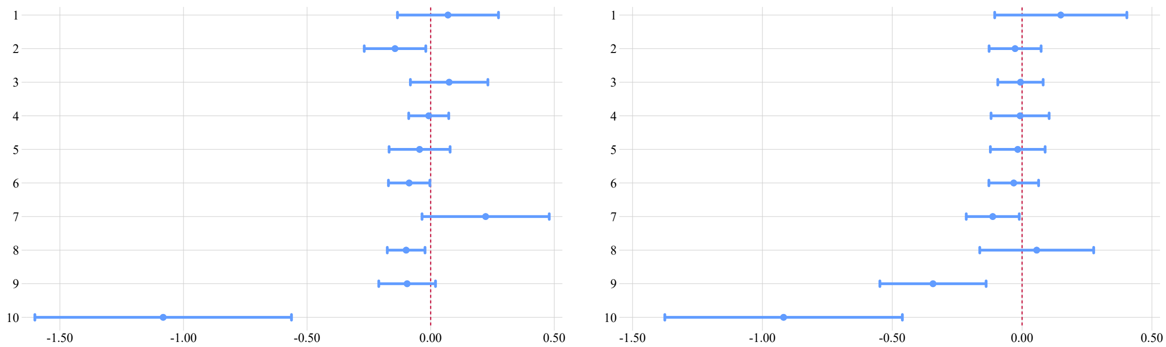
Larger firms are more sensitive to natural disasters

We start by looking at the role played by the global footprint of the supplier 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 1.08 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 0.92 buyers and suppliers between the 8th and 9th decile loose 0.34 buyers. 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 a supplier-time fixed effect.

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 specified by Antràs (2020), costs associated with establishing trade linkages are central to explaining the short and medium-term response of Global Value Chains to shocks. Such costs are sunk by nature. 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 higher the switching costs to 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 goods.

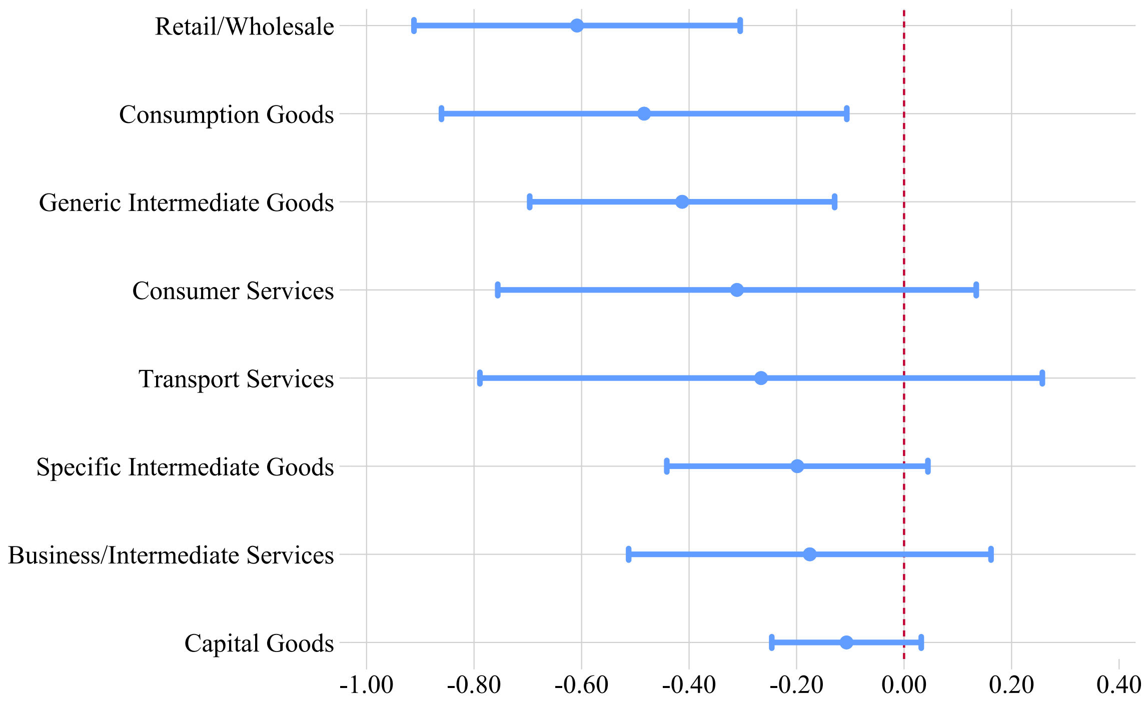
To explore this mechanism, we construct a measure of the good and service specificity using as proxy the sub-sector of the French exporters. We use the four-digit NACE classification and match it with the BEC classification to establish eight types of goods and services: capital goods, consumption goods, generic intermediate goods, specific intermediate goods, retail and wholesale, consumer services, business services and transport services.[7] We conduct the same analysis as before using the de Chaisemartin and d'Haultfoeuille (2020) estimator on sample restricted on 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 business services. Partnerships around the latter types involve greater sunk costs. Therefore, suppliers of such specific goods and services and their buyers will tend to protect their relationship to avoid greater losses and save this initial investment.

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

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

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



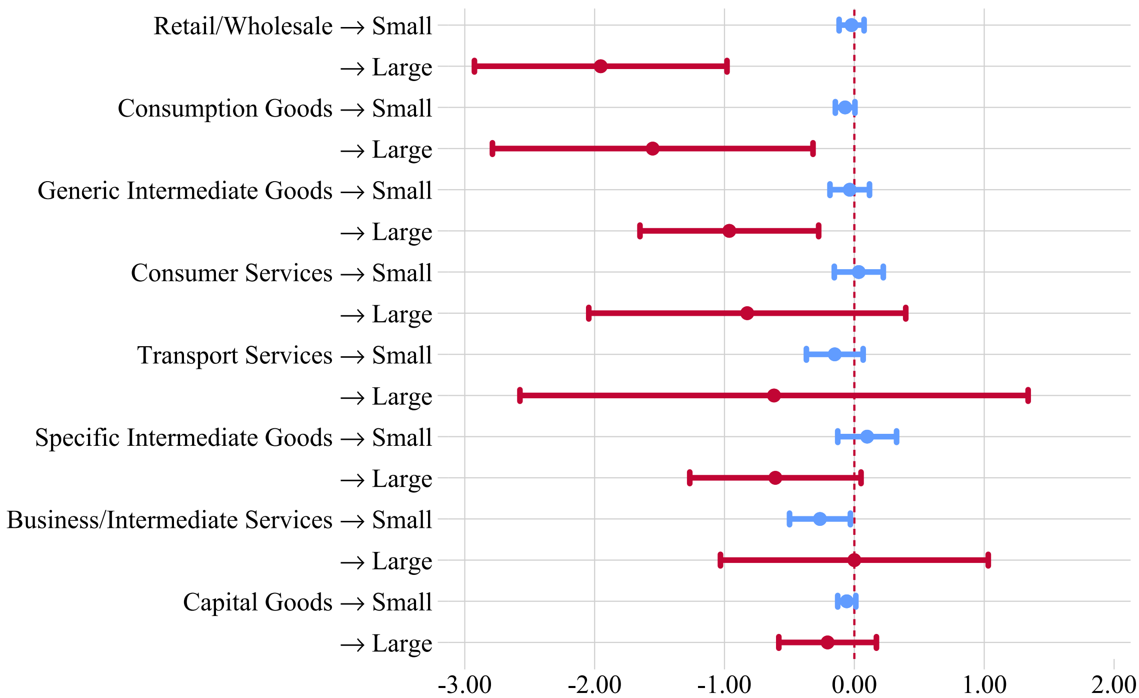
NOTE: Coefficients and 99% confidence interval are reported for two years after the disaster using the de Chaise-martin and d'Haultfoeuille (2020) estimator on sub-populations that includes exporter-buyer pairs where exporters belong to the category of interest. Firms are sorted into categories based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

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 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 1.95 buyers two years after the disaster whereas large firms producing specific intermediate goods or services loose 0.61 and 0.00001 buyers respectively.

3.4 Net Supplier Effect: Trade Diversion Rather Than Trade Destruction

We've established that natural disasters decrease trade flows into affected locations. We now investigate whether this results in net trade destruction at the firm level. Suppliers might be able to divert trade toward unaffected destinations. In this section, we compare the dynamics of trade credit and exports for suppliers that suffered from a disaster in one of their export markets

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 region-sector-time fixed effect.

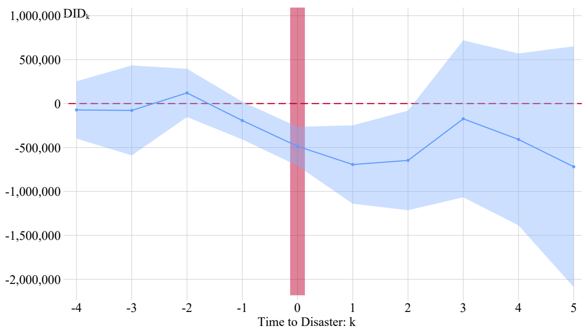
with suppliers that did not. We consider that suppliers are affected by a natural disaster if one of their export market is hit by a natural disaster as defined in section 2 and if that export market made up more than 10% of the supplier total trade credit exposure. For suppliers that suffered multiple 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 supplier and a time fixed-effect. We present the results in Figure 14.

We highlight two key results. First, trade credit exposure and buyers under trade credit terms decline, respectively by 646,941 EUR (panel 14a, 10.7% of the average exposure per supplier in the sample) and 7.8 buyers (panel 14b, 13.3% of the average number of buyers per supplier in the sample) after two years. [8] Second, exports remain relatively unaffected (panel

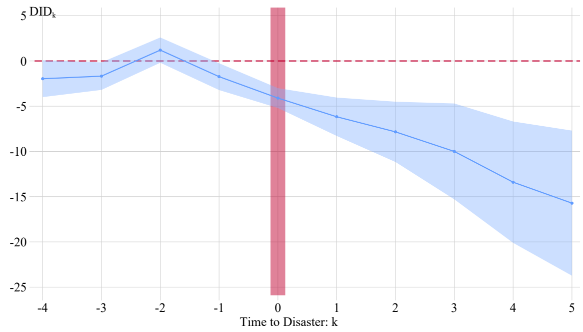
[8]Because of the differences in the event definition, the estimates are not directly comparable to the destination

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

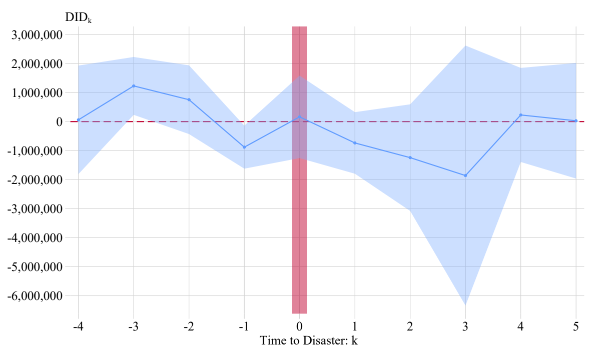
(a) Trade Credit (Euros)



(b) Number of Buyers



(c) 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 individual supplier fixed effects and time fixed effects. 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. 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 14c, the outcome variable is total value of exports. See Appendix D for the details on the computations of those variables.

14c) and revert back toward their pre-disaster level within four years. We interpret this such that following a disasters suppliers decrease sales toward affected locations and increase them toward unaffected locations. However, given the overall decrease in trade credit, those new sales are not financed by trade credit.

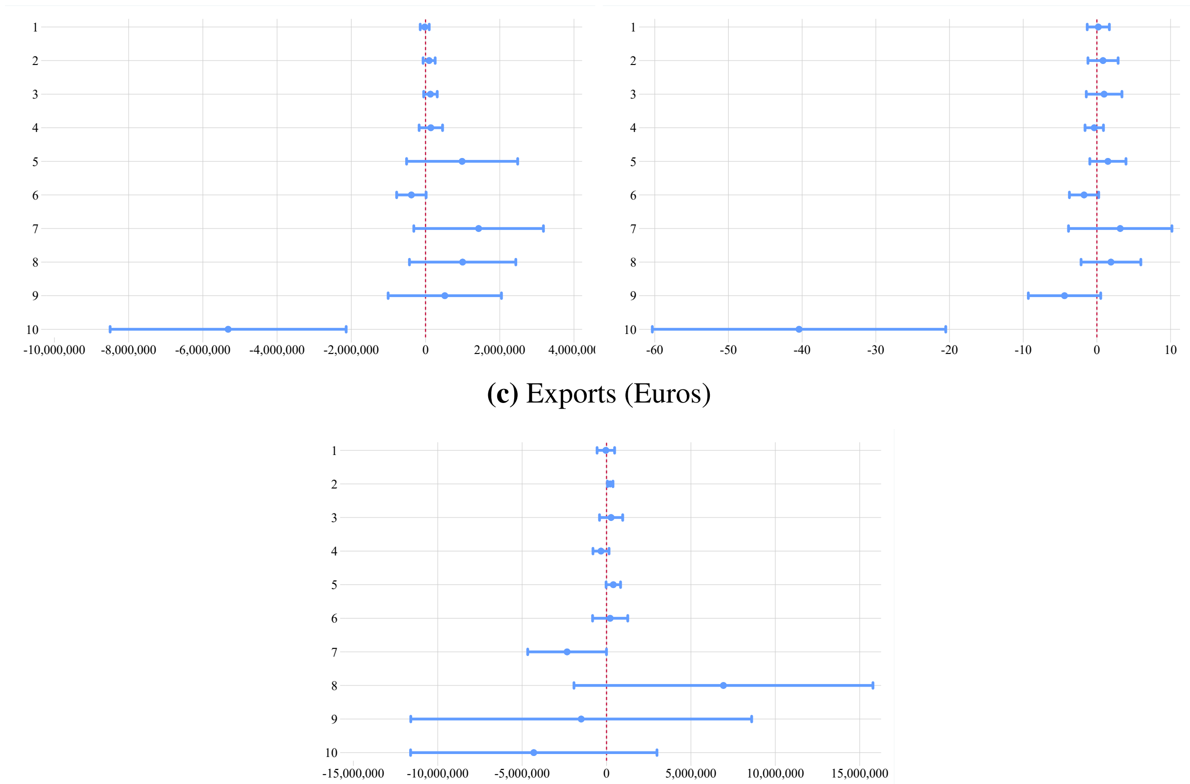
We now investigate whether this effect is stronger for suppliers with a larger global footprint. Intuitively, firms with many buyers in unaffected destinations should find it easier to compensate for the losses in the affected destinations. Figure 15a and Figure 15b show that while the largest suppliers are the ones experiencing most of the effect in trade credit exposure,

level results in Section 3.1

they do not display a significant response in the amount they export (Figure 15c). 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.

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 2010 and 2019, 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.

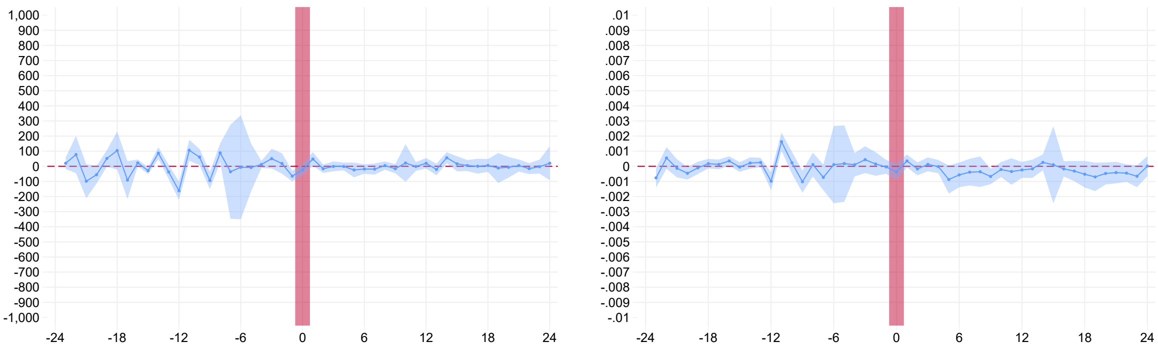
4 Robustness

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. 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



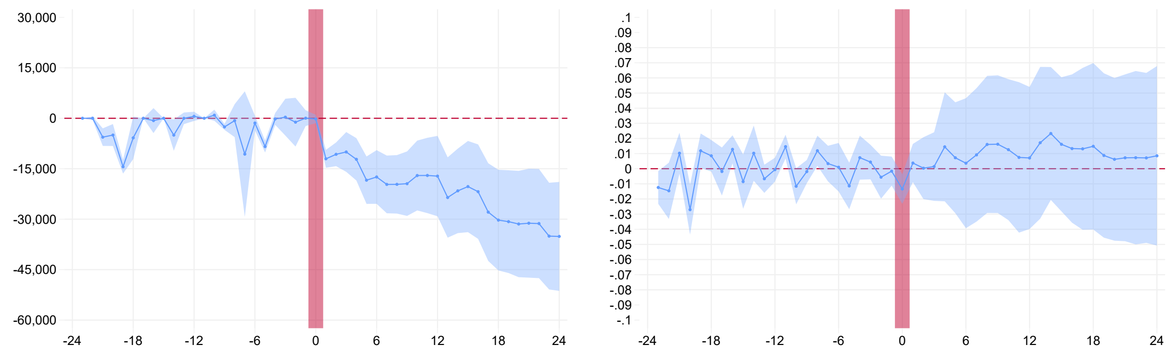
NOTE: These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 4. We include here a region-sector-time fixed effect. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue lines. Events 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 the effect to be small (lower than 1 percentage point change) and not statistically significant. 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

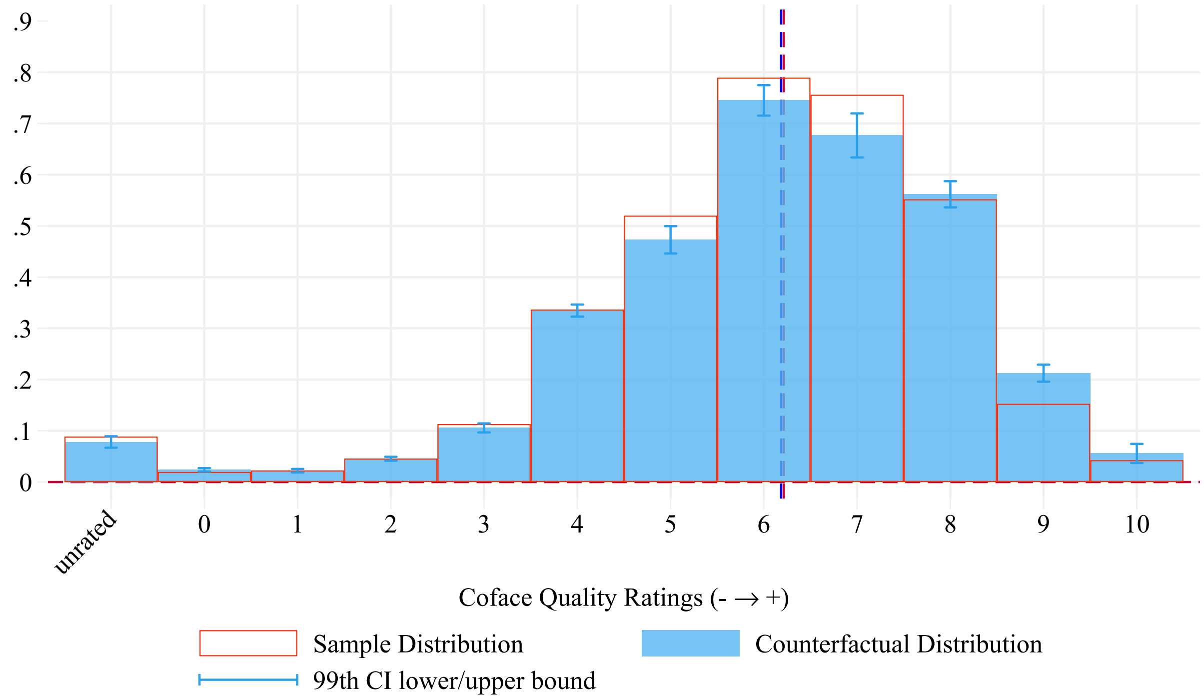


NOTE: These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 5. We include region-sector-time fixed effects. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue lines. Events are 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 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.

Figure 18: Effect of Natural Disasters on Buyer Quality after 2 Years



NOTE: These figures present estimates of the coefficient $DID_{k=1,k=2}$ associated with natural disaster events from estimating Equation 5. We include 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. 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). 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 either 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 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 diversion of trade within the supplier's network and little net 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 few buyers rather than suppliers with many buyers. 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 Disaster Types

A.1 Definition

Table 4: Disaster Types

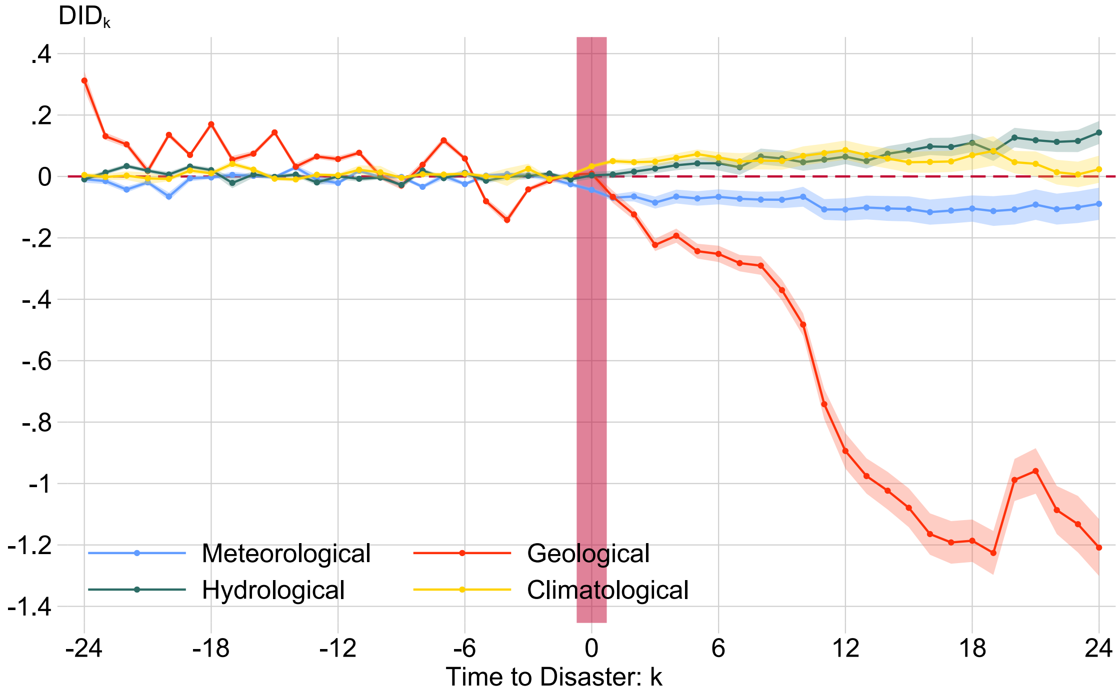
Disaster Group	Disaster Main Type
Geophysical	Earthquake, Mass Movement (dry), Volcanic activity
Meteorological	Extreme Temperature, Fog, Storm
Hydrological	Flood, Landslide, Wave action
Climatological	Drought, Glacial Lake Outburst, Wildfire
Biological	Epidemic, Insect infestation, Animal Accident
Extraterrestrial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

A.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 19. 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 19: 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 fixed effect. 99% error bands, computed with robust standard errors clustered at the firm-time level, are displayed as light lines. Events are defined as natural disasters above the median in terms of damage for the four main types of disasters. For countries with multiple disasters in between 2008 and 2019, we consider only the largest one. The outcome variable is the number of buyers purchasing from the supplier at credit.

B Alternative Estimator: two-way fixed effect

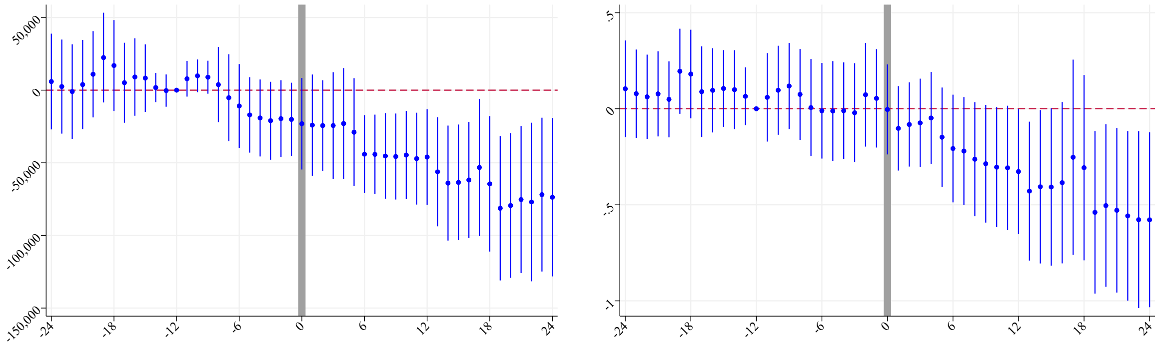
We use a fully dynamic saturated two-way fixed effect estimator as in Borusyak and Jaravel (2017). It accounts for both permanent differences across suppliers and common shocks between suppliers. We test how natural disasters change the structure of the supplier's network of buyers. Formally, we estimate the following equation:

$$Y_{f,j,t} = \sum_k \beta_k E_{j,t} + \gamma_{j,f} + \gamma_{t,r,n} + \upsilon_{f,j,t} \tag{6}$$

where f indexes the suppliers, j the countries, n the 2-digit industry, r the region and t the month. $E_{j,t}$ indicates that a natural disaster occurred in country j at time t. k indexes the months relative to the date of the event E. Y is the supplier's network in country j: number of

Figure 20: Effect of Natural Disasters on Exposure

(a) Amount of Exposure **(b)** Share of Affected Country



NOTE: These figures present estimates of the coefficient β_k associated with natural disaster events from estimating this equation: $Y_{f,j,t} = \sum_k \beta_k E_{j,t} + \gamma_{j,f} + \gamma_{t,r,n} + \upsilon_{f,j,t}$. 99% error bands, computed with robust standard errors two-way clustered at the country-period and country-supplier 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 amount in euros of trade credit insurance for a given supplier in the affected country in Panel 5 and the share of that country in the total exposure of each supplier.

buyers, exposure per buyers, total exposure, etc. $\gamma_{j,f}$ and $\gamma_{t,r,n}$ are respectively firm-destination and month-region-industry(2-digit) fixed effects. We use two-way clustering of the standard errors: country-time and country-supplier

We show the estimated coefficient β_k in Figure 20. We find a pattern of results that closely follows our key result in Figure 5c.

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.