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# Trade Networks and Natural Disasters: Diversion, Not Destruction

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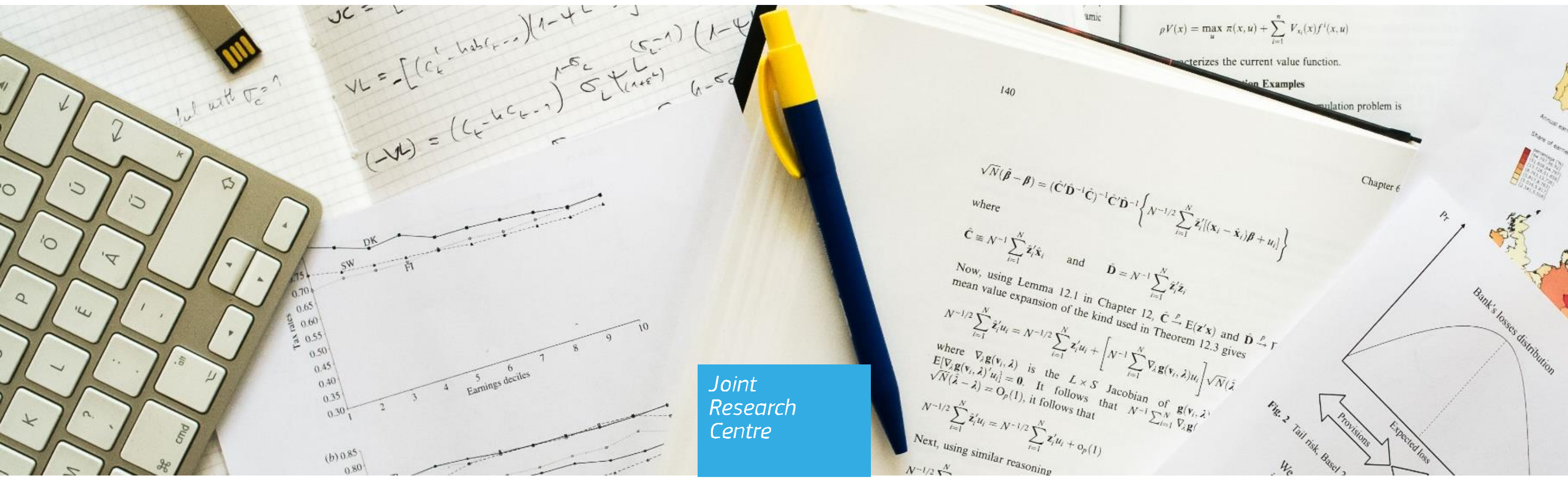

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## Executive summary

We establish the causal effect of natural disasters abroad on the size, shape and quality of French exporters' international trade networks.

Since the 1970's, natural disasters have increased in both frequency and severity. This has led to wide-scale destruction of public infrastructures, physical capital and durable consumption goods. By durably disrupting international buyer-supplier relationships, natural disasters may delay economic recovery in affected countries and make it more costly. Natural disasters affects international trade networks through a combination of damage to the country's production apparatus and transport infrastructure.

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 result in fewer matches between buyers and suppliers. Less firms will be productive enough to pay the additional costs to take part in international trade. The impact 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 effects and therefore to an increase in quality (in terms of productivity and financial health) of "surviving importers". At the same time, the negative productivity shock to all potential buyers should lead to a lower quality among incumbent buyers. Still, larger suppliers and buyers have more opportunities to divert their trade to unaffected countries. In this paper, we test empirically those theoretical predictions and study the resilience of trade networks to natural disasters.

### *Methodology*

We use a dynamic difference-in-differences identification strategy. We employ the Chaisemartin & D'Hautefeuille (2021) 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.

### *Data*

We use novel firm-to-firm trade credit data from one of the top three international credit insurers (Coface). We pair this data with custom data on French exporters from 2010 to 2019 and exhaustive worldwide disaster data from EM-DAT.

### *Main Findings*

We find evidence of large and persistent disruptions to international buyer-supplier relationships. This prompts a restructuring of the trade network of the largest French exporters and a change in trade finance sources for affected countries. French suppliers decrease their trade credit sales to affected countries. Suppliers reduce their trade credit exclusively through the extensive margin by reducing their number of clients rather than the amount per client. This effect is particularly strong for goods and services with lower level of specificity.

We show that that this effect is characterised by two-sided granularity. Larger firms display greater sensitivity to natural disasters, both on the supplier and on the buyer side. Suppliers above the ninth decile of size (measured by their initial worldwide trade credit sales) drive most of the observed average. On the buyer side, when differentiating across credit risk assessments at the time of the disaster, we find that the fall is greater for buyers of medium to high credit quality. Higher credit quality buyers are typically larger firms due to Coface assessment methodology. Their exit mechanically decreases the average quality of the network.

Additionally, we find that natural disasters lead to reallocation between clients and trade diversion between countries. Larger networks shrink and become denser. Our results reflect a lower cost for bigger firms to restructure their network. Bigger suppliers can more easily switch away from the affected country without fully losing access to this export market. They have already access to a well-structured network of alternative buyers in other destinations without incurring additional search cost. It is also easier for them to use alternative types of trade financing thanks to their relatively stronger bargaining power. Overall, our results indicate that natural disasters mostly induce a reshaping of the trade networks of the largest exporters and largest buyers and a shift away from trade credit toward cash in advance in affected markets rather than a permanent destruction of trade.

# 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 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 the largest French exporters and a change in trade finance sources for affected countries. We find strong and permanent negative effects on the trade credit sales of French suppliers to affected destinations. The largest firms are driving the response, both on the supplier and buyer side. Trade network restructuring towards unaffected destinations is higher for large multinationals trading more homogeneous products. This effect operates exclusively through a reduction in the number of buyers. This induces a negative shift in the distribution of the quality of buyers in the destination affected by the natural disaster.

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

**Keywords:** Firm Dynamics; Trade Networks; Natural Disaster, Granularity.

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# 1 Introduction

Cross-border buyer-supplier relationships is a costly investment for both parties. Disruptions to those international trade linkages carry high economic costs. Since the 1970's, natural disasters have increased in both frequency and severity. This has led to wide-scale destruction of public infrastructures, physical capital and durable consumption goods. By durably disrupting international buyer-supplier relationships, natural disasters may delay economic recovery in affected countries and make it more costly. Moreover, the shock may propagate across borders through global value chains, with suppliers in unaffected countries bearing some of the costs. In this paper, we study the resilience of trade networks to natural disasters.

Natural disasters affects international trade networks through a combination of damage to the country's production apparatus and transport infrastructure. Damages in terms of GDP can be substantial, ranging from 2.9% of the affected country's GDP at the $75^{th}$ percentile of the distribution of disasters to 56% at the $95^{th}$ percentile. 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 result in fewer matches between buyers and suppliers. Less firms will be productive enough to pay the additional costs to take part in international trade. The impact 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 effects and therefore to an increase in quality (in terms of productivity and financial health) of "surviving importers". At the same time, the negative productivity shock to all potential buyers should lead to a lower quality among incumbent buyers. Still, larger, more flexible, suppliers and buyers have more opportunities to divert their trade to unaffected countries. Bricongne et al. (2022) have shown how larger firms are also the ones reacting more strongly to macroeconomic shocks, driving the aggregate response.

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 from 2010 to 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 prompts a restructuring of the trade network of the 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 amounts have declined by 8.7% (€27,000). Suppliers reduce their trade credit exclusively through the extensive margin by reducing their number of clients rather than the amount per client. The number of clients drops by 6.9% (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 particularly strong for goods and services with lower level of specificity. We show that that this effect is characterised by two-sided granularity. Larger firms display greater sensitivity to natural disasters, both on the supplier and on the buyer side. Suppliers above the ninth 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. On the buyer side, when differentiating across credit risk assessments at the time of the disaster, we find that the fall is greater for buyers of medium to high credit quality. Higher credit quality buyers are typically larger firms due to Coface assessment methodology. Their exit mechanically decreases the average quality of the network. However, disasters are not followed by a rise in insolvencies in affected destinations. Additionally, we find that natural disasters lead to reallocation between clients and trade diversion between countries. For instance, trade in goods is not as much affected as the number of clients using trade credit: the effect size and persistence is much lower. We also find that after a disaster, there is no increase in the probability that a supplier completely leaves an affected destination.

Instead larger networks shrink and become denser. When looking at supplier-level outcomes we find evidence that trade credit and trade in goods levels recover at least partially within a few years but the number of buyers does not. We interpret those different results as reflecting a lower cost for bigger firms to restructure their network. Bigger suppliers can more easily switch away from the affected country without fully losing access to this export market. They have already access to a well-structured network of alternative buyers in other destinations without incurring additional search cost. It is easier for large multinationals who benefits from a wide range of destination countries to divert the extra trade to other destinations and already-existing buyers. It is also easier for them to use alternative types of trade financing thanks to their relatively stronger bargaining power. *Overall, our results indicate that natural disasters mostly induce a reshaping of the trade networks of the largest exporters and largest buyers and a shift away from trade credit toward cash in advance in 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) or in Malgouyres et al. (2019) following a large positive technological shock. More recently however, Bricongne et al. (2022) find that most of the adjustment

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

to the Great Financial Crisis and the COVID pandemic happened through the extensive margin. Additionally they find, in line with our results, that the largest exporters exhibits a higher sensitivity to macro-economic shocks in the destination country. Thanks to the detailed nature of our data, our paper provides clues as to why: we find that this higher elasticity is driven by some of the largest clients leaving the network of the largest suppliers.

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 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. Section 3 shows our baseline results and develops on the granularity of the effect. Section 4 describes the restructuring of the network. 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.

**Table 1:** Sample Descriptive Statistics

| | N | Mean | Median | Std.Dev. |
|---|---|---|---|---|
| *Panel A Supplier-Destination Coface* | | | | |
| Monthly Trade Credit (K EUR) | 12,150,762 | 309.72 | 20 | 2117.61 |
| Number of Debtors | | 3.02 | 1 | 14.80 |
| Exposure per Debtor (K EUR) | | 108.15 | 50 | 702.44 |
| Requested Amount (K EUR) | | 430.16 | 25 | 3088.32 |
| Defaults (K EUR) | 23,538 | 1.04 | 1 | 0.20 |
| Amount of Defaults (K EUR) | 23,538 | 39.01 | 11 | 144.51 |
| *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) | 603,390 | 12.74 | 8 | 14.66 |
| Destinations (exports) | | 7.91 | 5 | 9.17 |
| Number of Debtors | | 60.73 | 16 | 170.04 |
| Monthly Trade Credit (K EUR) | | 6237.01 | 838 | 31367.50 |
| Monthly Exports (K EUR) | | 1601.66 | 158 | 15045.02 |

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.3 for the details on the computations of those variables.

Our dataset includes every French suppliers which has 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 assessment 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 €20,000 and a mean of €309,720, the distribution of this variable is highly skewed. The number of buyers per destination is characterised by a large standard deviation (14.8) 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 23,538 are recorded in our database, although some of those are fairly large (standard deviation of 144,510). 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 produces assessments of credit quality of buyers. Those assessments are based on a combination of fiscal data, experts opinions and external assessments. An assessment of 0 is the lowest possible. An assessment of 10 indicates that the buyer's "performance solidity is undoubted".[2] We note that both unrated and the "0" category are not as homogeneous as other assessment 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. We show in Figure 24 in appendix how those assessments are positively correlated with net turnover. We take the examples of French firms for which we have both Coface assessments and turnover data [3]. We see that highest credit quality firms are on average larger.

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

[2]Internal Coface documentation.

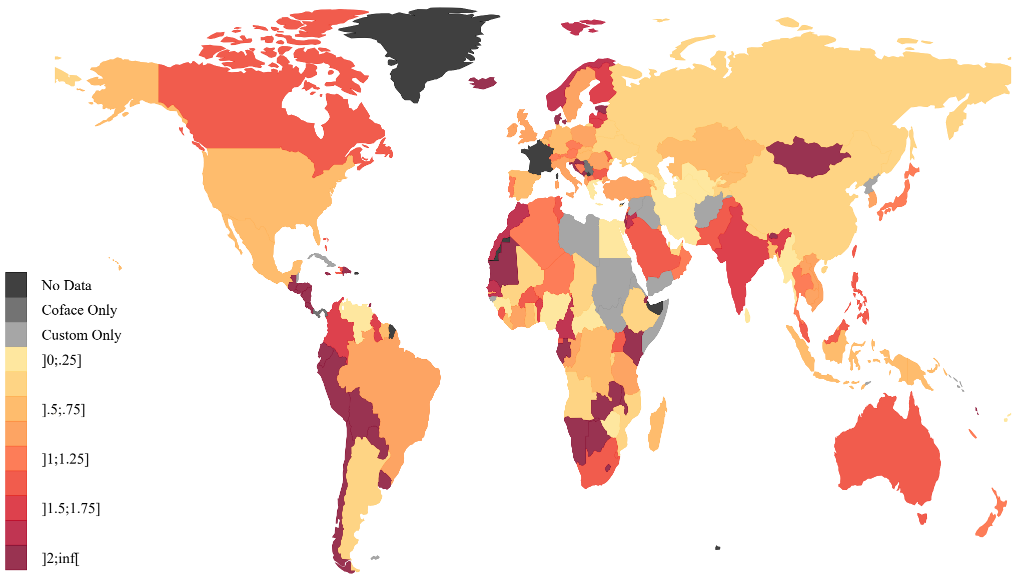
[3]Turnover is computed using the FIBEN balance sheet data collected by the Banque de France.

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 D.4.

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 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 more coverage than the amount actually needed. In turn, 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.

[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." (Muûls, 2015)

**Figure 1:** Trade Credit to Customs Data Coverage




Note: This figure presents the ratio of trade credit to goods and merchandise sales for French exporters as reported by Coface and the French Customs respectively.

### 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, 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.

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

We follow Fratzscher et al. (2020) in the construction of the event variable. We first scale reported damage by previous year GDP:

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

An event is selected 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 16 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 two alternative definitions of events. We take either the first big event rather than the worst one in a country, or we select the worst events greater than the third quartile globally rather than the median threshold. 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 17. The only positive and statistically significant coefficient is the one contemporaneous to the recorded event. It shows that the event variable is not capturing damages 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 D.1.

**Table 2:** Sample Descriptive Statistics

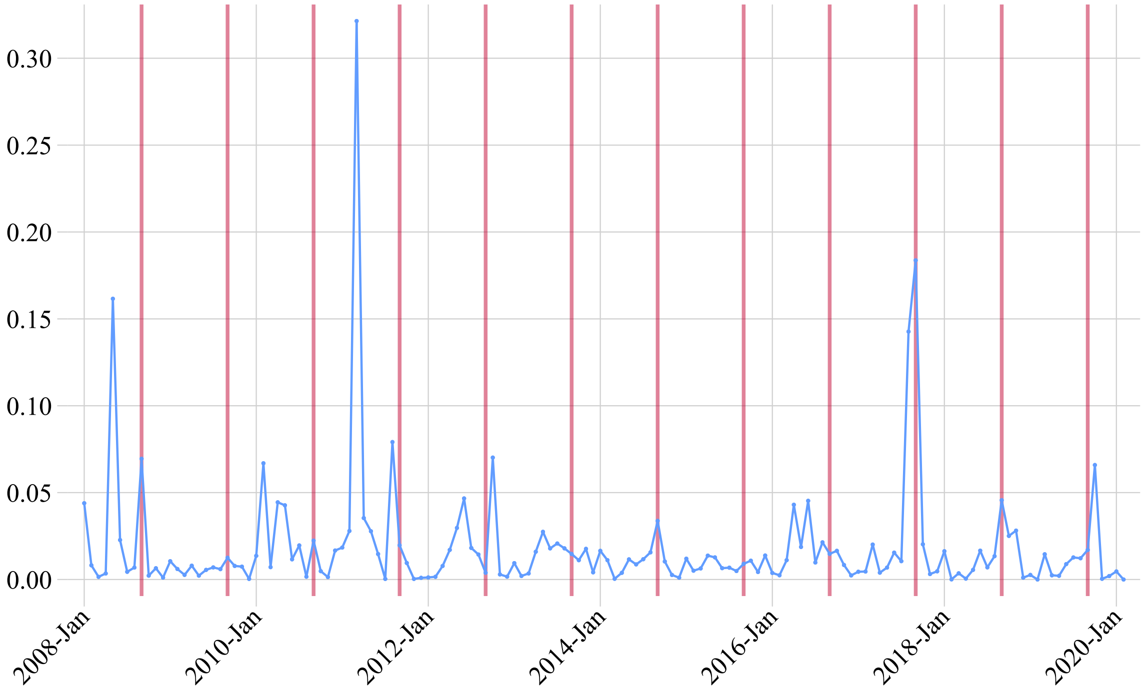
| | N | Mean | Median | Std.Dev. |
|---|---|---|---|---|
| *All Disaster Types* | | | | |
| Estimated Damage (USD Mn.) | 92 | 7278.92 | 500.00 | 28409.59 |
| Estimated Damage (% GDP) | 92 | 8.73 | 0.77 | 30.61 |
| *Type = Climatological* | | | | |
| Estimated Damage (USD Mn.) | 9 | 1309.08 | 500.00 | 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 main definition of event as described in 2. See Table 4 in appendix D.1 for the details on the type of disasters.

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 light blue are excluded from the treatment group because their worst events are contaminated by repeated events. We recycle their untreated periods to increase the size of the control group. Countries in shades of 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).

**Figure 2:** Natural Disasters

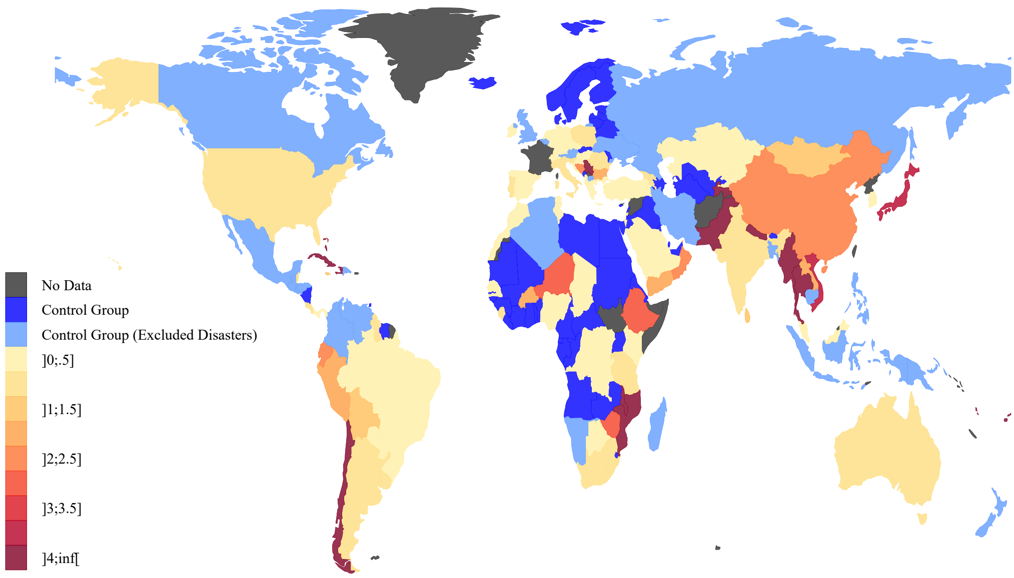



Note: This figure presents estimated damage in percentage of GDP caused by natural disasters. The source for the disaster data is EM-DAT. Authors' computations.

### 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 12,150,762 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 146,844 distinct supplier-destination linkages in 181 different countries. Of those supplier-destination dyads, 57,915 (39%) are never treated. The rest suffers from a natural disaster at some point during the sample period. On average about 0.5% 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.

**Figure 3:** Geographical Distribution of Natural Disasters Events




Note: This figure describes the distribution of countries between the permanent control group in blue and the treated group in shades of red that is affected at different time. The shades of red indicates the severity of the disaster in damage per GDP. Countries in light blue are excluded from the treatment group because their worst events are contaminated by repeated events. The source for the disaster data is EM-DAT

**Table 3:** Estimation Sample

| Level | N |
|---|---|
| Months | 120 (2010m1-2019m12) |
| Destinations | 181 |
| Suppliers | 9,615 |
| Dyads (firms * destination) | 146,844 |
| ↪ Ever treated | 88,929 |
| ↪ Never treated | 57,915 |
| Observations | 12,150,762 |

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.

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:

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

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 level of $Y$ is determined by some time varying components at the supplier ($\gamma_{f,t}$) and the region-sector level ($\gamma_{r(j),s(f),t}$), common to certain groups of observations regardless of their treatment status. Those could be the business cycle in the sector and region of destination or supplier-specific productivity shocks. The estimation of $\beta^k$ 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 $\beta^k$ 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. Finding new buyers will prove more costly for those suppliers. We, therefore, expect that higher specificity moderates the effect of a disaster with decreasing $\beta^k$ based on the level of specificity in each sub-sample.

To estimate $\beta^k$, 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 Chaise-martin 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. In our empirical setup, the identifying assumption is that suppliers operating in affected and unaffected countries would have had on average 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, when we estimate pre-treatment coefficients 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: sector-region-time and firm-time. $N_t^k$ 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 of $DID_{t,k}$. The former accounts for common shocks across suppliers in a given market (here a NACE 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 accounts for possible 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 $\Delta Y$ 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 the frequency of "zero flows" to increase in affected destinations in the aftermath of a disaster. Dropping those observations would bias $DID_{t,k}$ toward zero.

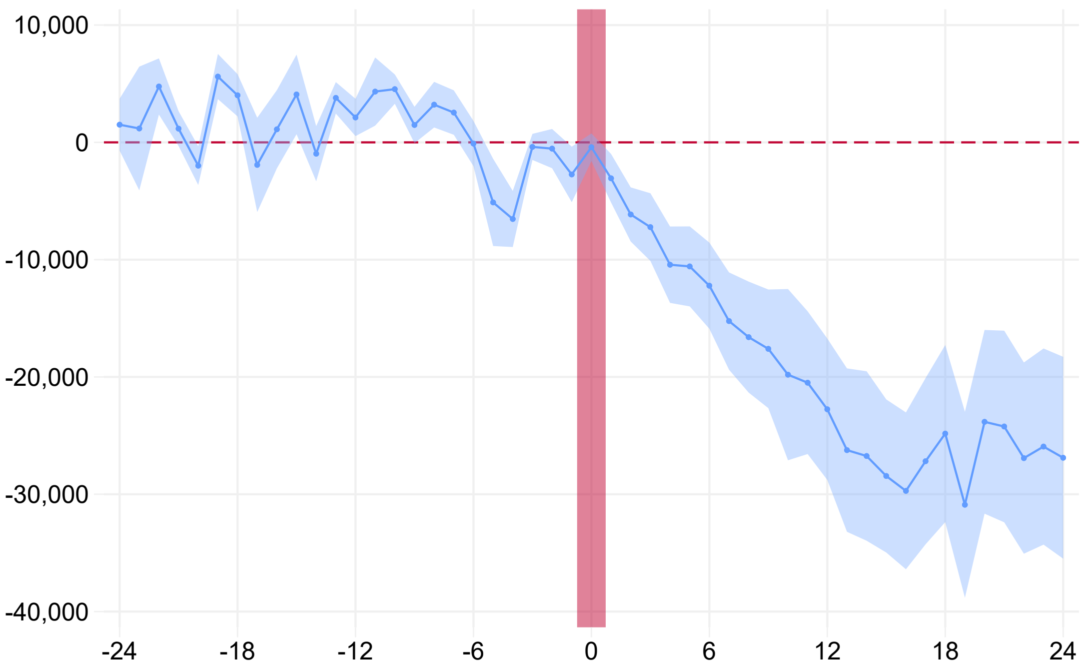
# 3 The buyer margin and the granular effects of natural disasters

We first show in section 3.1 how natural disasters impact the size and shape of suppliers' network in affected countries. We highlight how this effect is very granular on the supplier side in 3.2. We then show that such granularity is also visible on the buyer side in 3.3.

## 3.1 Large and persistent decline of the buyer margin

We first present our result on the effect of natural disasters 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 €309,720 (P50 = 20,000). The total loss after 24 months represents a 7.3% (12 months) and a 8.7% (24 months) decrease in trade credit exposure to the affected destination relative to the sample mean.

**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 4. The outcome variable is the amount in euros of trade credit insurance for a given supplier in the affected country. 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 a 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. See Appendix D.3 for the details on the computations of the dependant variable.

### 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 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 credit exposure per trade credit buyer in the destination country. We provide details on the computations of those variables in Appendix D.3.

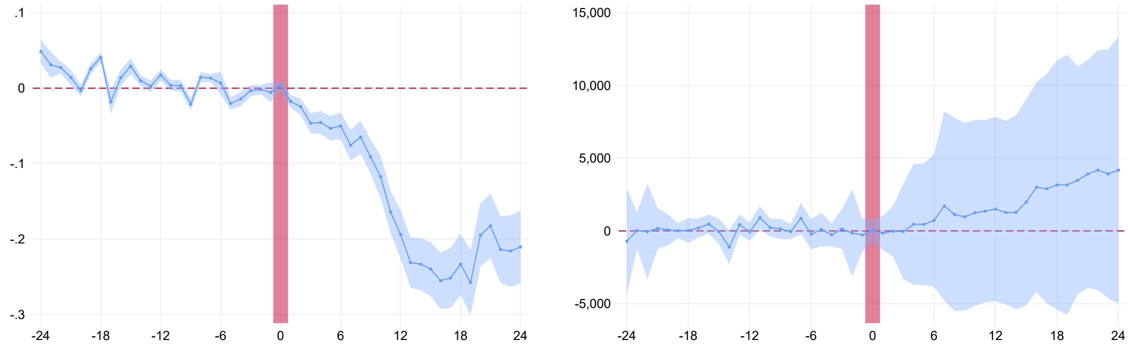
In Figure 5, we show that the impact is driven by the buyer margin, i.e. the number of clients rather than the exposure per client. The effect increases from about from -0.16 buyers after 12 months to -0.21 buyers after 24 months and is robust to the inclusion of both supplier-time fixed effects and sector-region-time fixed effects (Figure 5a). The average number of buyers in the sample is 3.02 (P50 = 1). This represents a 6.9% decline in the number of buyers using trade credit 24 months after a disaster. Meanwhile, we find no negative impact on the intensive margin (Figure 5b). If anything, while not statistically significant, the average trade credit per buyer has increased by €4,180 or 3.86% after 24 months.

We report results by various types of disasters in Appendix B.1. We decompose disasters according to their 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 still 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). These results reflect the heterogeneity in the extent of damages caused by each type of disaster.

**Figure 5:** Extensive and intensive margin

**(a)** Number of buyers with trade credit

**(b)** Trade credit / number of buyers



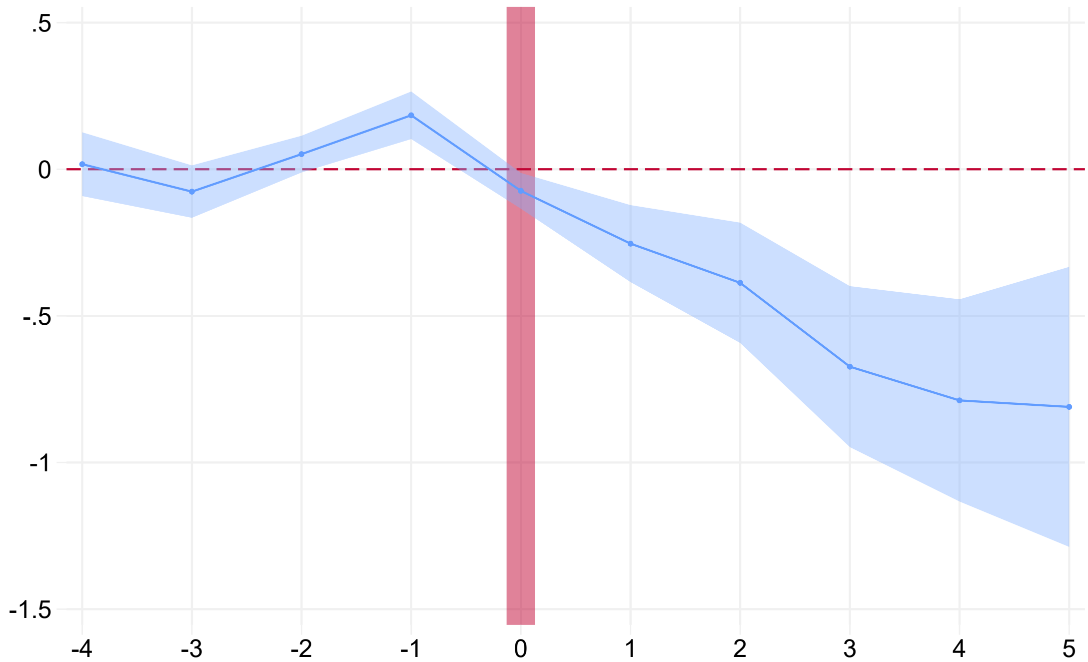

Note: These figures present estimates of the coefficient $DID_k$ associated with natural disaster events from estimating Equation 4. In Panel 5a, the outcome variable the number of buyers purchasing from the supplier at credit. Results are displayed including a supplier-time and sector-region-time fixed effects. In Panel 5b, the outcome variable is the average amount of trade credit per buyer in the affected destination. 99% error bands, computed with robust standard errors clustered at the region-sector level, are displayed as a blue area. 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. See Appendix D.3 for the details on the computations of the dependant variables.

### 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 first big disaster as an alternative definition of a disaster event (Appendix A.2.2), 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. We further confirm our result by checking that they do not reflect ex-ante differences between treated and non treated. In Appendix A.2.3, we repeat the estimation with the first big disasters but we exclude the never treated observations and use only the not-yet-treated dyads as control group. We find a very similar pattern of results with somewhat larger coefficients, the fall in the number of buyers reaching 2 buyers after 5 years. We 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.3).

Our results are robust to various definitions of the event variable and to potential differences between yet-to-be-treated and never-treated control observations.

**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 4 at the yearly level. The outcome variable is the number of buyers of trade credit insurance for a given supplier in a country. 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 a blue area. 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. See Appendix D.3 for the details on the computations of the dependant variables.

## 3.2 Supplier side granularity

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, size or financial constraints are likely to affect the choice to pivot toward unaffected destinations or maintain relationships with buyers in the affected destination.

### 3.2.1 Larger suppliers 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 lose 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 7. We measure size with either the initial total number of buyers (Panel 7a) or the initial total trade credit exposure worldwide (Panel 7b). In both cases we use the size at the time we first observe the supplier in our sample.

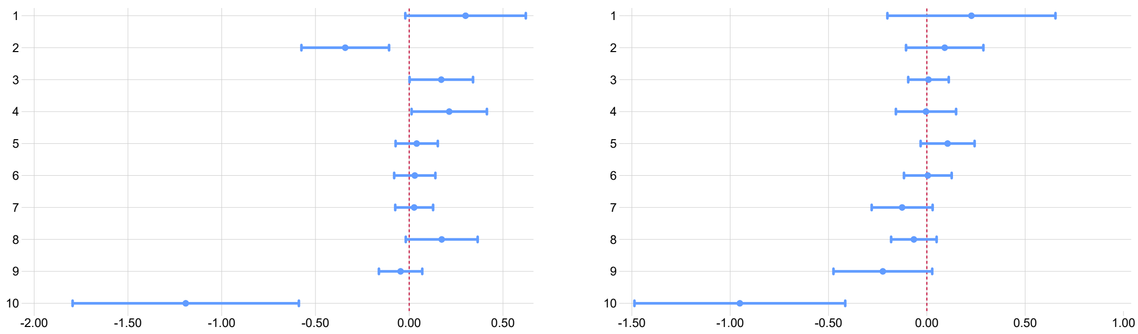
We find that the decline in the number of buyers is almost entirely explained by the outcome of suppliers at the very top of the size distribution. Suppliers above the last decile of numbers of relationships worldwide lose 1.2 buyers on average 2 years after the disaster. Meanwhile suppliers below the 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 lose 0.95 buyers and suppliers between the 8th and 9th decile lose 0.22 buyers, but slightly non-significant. Suppliers below the 8th decile do not exhibit any meaningful decline in buyers following a disaster.

### 3.2.2 Firms with highly specific output lose less buyers than firms with lower specificity.

The greater sensitivity of larger firms could reflect the fact that they are trading more homogeneous products that can be more easily diverted to new clients in new destinations. 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

**Figure 7:** Effect of Natural Disasters conditional on the supplier size (k=2 years)

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




Note: The outcome variable is the number of buyers under trade credit. 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 supplier-buyer pairs where the supplier belongs to the bin of interest. We include here supplier-time and sector-region-time fixed effects.

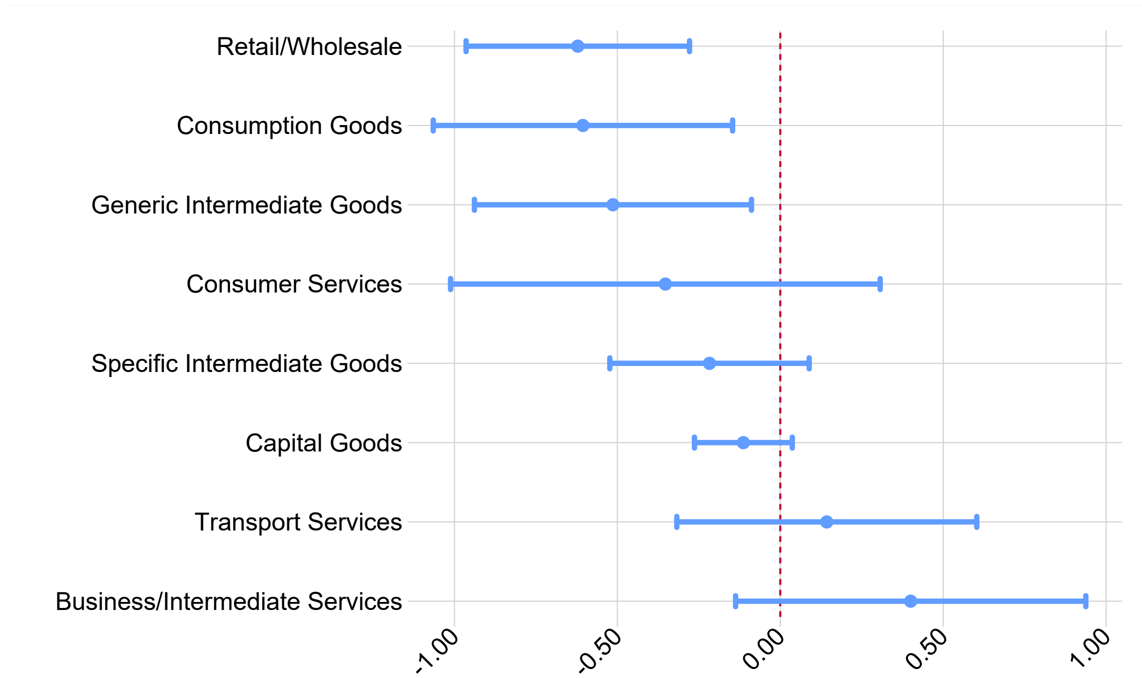
contractual security under incomplete contract enforcement, and, finally, the cost associated with the development of physical assets specific to the buyer-supplier relationship. The more specific a good or service traded between the two firms, the higher the sunk cost. Therefore, the higher the losses 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 weigh on the 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[6]. We conduct the same analysis as before using the De Chaisemartin and D'Haultfoeuille (2020) estimator on sub-samples restricted to exporters belonging to each of the above categories. Figure 8 synthesizes the hetero-

[6]See appendix D.4 for the full description of each category.

geneity in estimated response by category after two years. As expected, the negative response of the buyer margin observed on average is driven by retail and wholesale, consumption goods, and generic intermediate goods, while it is more muted for capital goods, specific intermediate goods and consumer and business services. The latter types, because of their relationship-specificity, 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 preserve their initial investment.

**Figure 8:** Effect of Natural Disasters conditional on supplier output specificity (k=2 years)

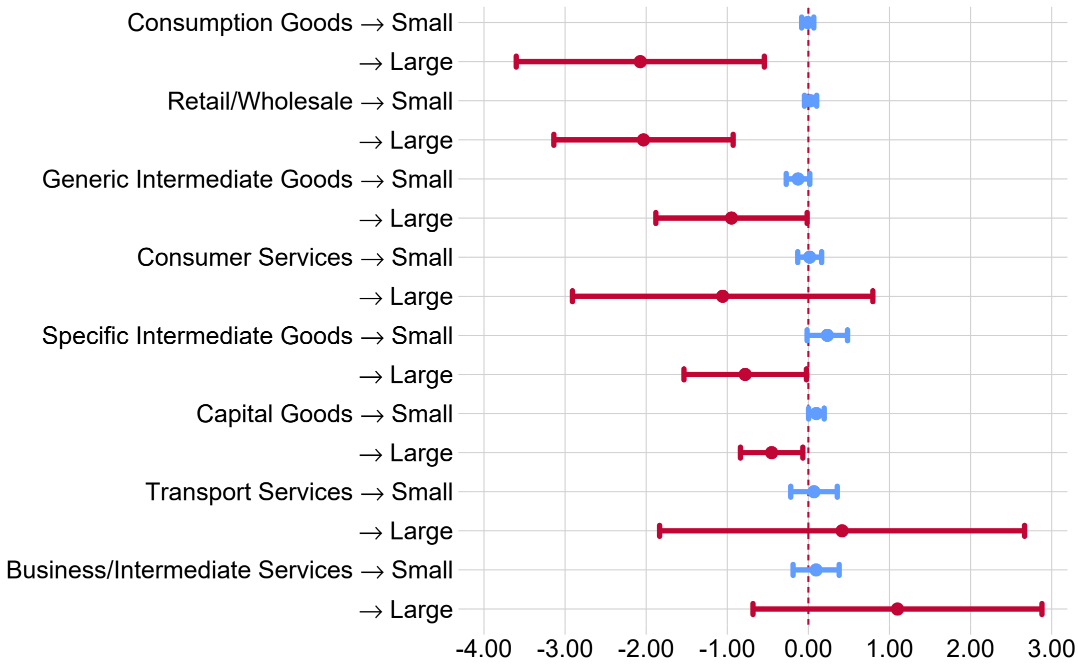



Note: The outcome variable is the number of buyers under trade credit. Coefficients and 99% confidence interval are reported for two years after the disaster using the De Chaisemartin and D'Haultfoeuille (2020) estimator on sub-populations that includes exporter-buyer pairs where exporters belong to 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.

### 3.2.3 For a given level of specificity, larger suppliers lose more buyers

We now investigate whether the effect of size persists within categories of specificity. We repeat the same estimation procedure as before in section 3.2.2 but we allow the estimated coefficient to vary both by product specificity and supplier size. The specificity categories are unchanged but for simplicity we sort firms within each category into only two 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 9. We note two facts. First, within each category except business and transport services, 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 lose 2.0 buyers two years after the disaster whereas large firms producing specific intermediate goods lose 0.77 buyers and those selling intermediate services are not significantly affected. These results confirm the presence of granularity in the effect of natural disasters on trade networks.

**Figure 9:** Effect of Natural Disasters conditional on supplier output specificity and size (k=2 years)




Note: The outcome variable is the number of buyers under trade credit. 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.

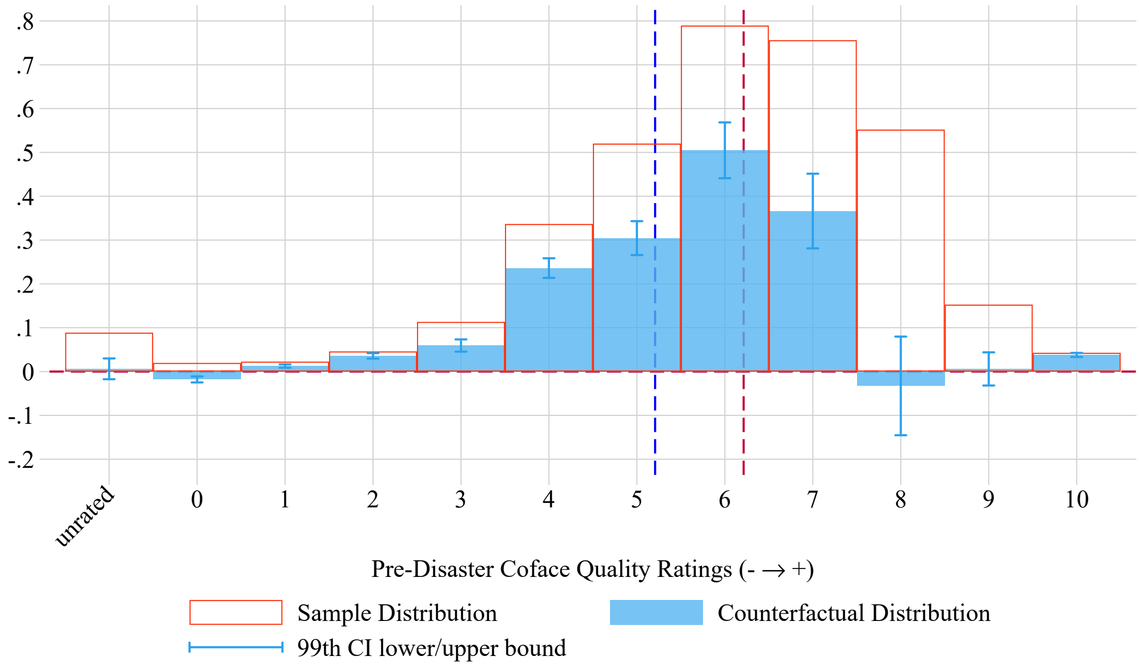
#### 3.2.4 Larger firms are also more sensitive to generic macro shocks

The greater sensitivity to natural disasters of larger suppliers was not obvious ex-ante. Owing to their size, they are better suited to weather the shock by keeping their client base but at the same they are ideally positioned to pivot away from the affected country. Interestingly Bricongne et al. (2022) find a very similar pattern in the reaction of large firms to common macro shocks. The deviation of the firm-level growth rate of their exports from the unweighted average growth rate of exports (the "macro shock") is systematically higher than for smaller firms. As a precaution, we reproduce their decomposition exercise on our dataset. Following their methodology, we compute the firm-level mid-point growth rate of trade volume, trade credit exposure and number of buyers. We separate aggregate export growth into two components: an average growth rate and a granular residual. The unweighted average growth rate is a measure of shocks common to all affected firms. The granular residual captures the size-weighted deviation of the firms' growth rate from the average growth rate for each variable. If the granular residual is positive it means that bigger firms react more to the shock. We plot in appendix C.3 the average growth rate and the granular residual for trade in goods (Figure 32a), trade credit exposure (Figure 32b) and number of buyers under trade credit terms (Figure 32c). First, we see that in all cases the granular residual is non-zero, with larger firms reacting more to macroeconomic shocks. Then, looking at the correlation between the average growth rate and the granular residual, we see a correlation of 0.60 for exports, which is close to the 0.55 found by Bricongne et al. (2022) in their longer sample (1993-2020 vs. 2010-2018 in this paper). It means that large firms tend to do worse than the average in bad times and better than the average in good times. When focusing on trade credit, we find a correlation equal to 0.39 for trade credit exposure and 0.70 for the number of buyers under trade credit terms. This greater correlation for the number of buyers than for the amount of trade credit is in line with our results from section 3.1.1. This result confirms that the buyer margin is driving most of the effect, with larger exporters losing more buyers than the average in difficult times. This also extend our main result from fairly specific natural disaster shocks to more generic macro shocks. Additionally, we expand Bricongne et al. (2022) by showing that their result holds true for trade finance flows.

### 3.3 Buyer side granularity and the decline in quality of the network

Having uncovered the granularity of the response on the supplier side, we now turn to the buyer side. The detailed nature of the data allows us to check for the presence of buyer side granularity. While we do not directly observe the size of the foreign buyers, we may proxy it using Coface internal assessments of buyers. According to a separate sample of French buyers for which we have both a assessment and balance sheet data, the assessments are strongly correlated with size (see Figure 24 in appendix). To neutralize the effect of disasters on assessments, we freeze each buyer's assessment at the time of the disaster and then count each year the number of buyers still active from each initial category. We compute this variable such that: $T^r_{j,f,t} = \sum \mathbf{1}(TC_{j,b,f,t} > 0 \cup R_{b,k} = r)$ with $k$ the month of the event and $r$ the credit rating assessment. We estimate the effect of natural disasters on the number of buyers per supplier in each assessment 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 show the results in Figure 10. The bins in red represent the sample average number of buyers in each assessment category. The bins in blue represent the counterfactual average number of buyers per category after subtracting the coefficient from the sample average. First, Figure 10 shows that not all categories are affected similarly. The losses are greatest among the large and highly rated buyers at the time of the event (assessments from 7 to 9 with 8 being the most impacted). Clients in categories 1 and 2 are essentially unaffected whereas those in categories 3 to 5 are only moderately affected. As on the supplier side, we once again show that larger firms are more sensitive to a macro shock. Second, we find that this granular reaction induce a negative shift in the distribution of buyer quality two years after the event. The average assessment before the shock is 6.2 (the red dash vertical line) and declines to 5.2 two years later (the blue dash vertical line). Not only is the typical network of clients smaller, it also includes relatively more clients that were more badly rated before the disaster.[7]

**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 two years after a natural disaster event, from the estimation of 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 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 assessment category taken at the time of the event. We plot the sample distribution of assessments in red and its counterfactual distribution in blue.

# 4 Net Supplier Effect: A Restructuring of the Network

We've established that macroeconomic shocks at the country level durably lower the number of buyers in the destination country. This response to natural disasters exhibits double-sided granularity: larger suppliers lose more clients and larger clients are the most likely to leave the supplier's network. In this section, we show that this pattern is partially moderated by reallocation between clients and trade diversion effects between countries. First, trade in goods is not as much affected as trade credit: the effect size and persistence is much lower. Second, we

[7] In Appendix B.5, we present the results without freezing the assessments at the time of disaster.

find that after a disaster there is no increase in the probability of leaving an affected destination. Instead the larger networks in the country shrink. Third, when looking at supplier-level outcomes we find evidence that trade credit and trade in goods levels recover at least partially within a few years but the number of buyers does not. Networks becomes denser. Fourth, while the supplier-level number of clients and trade credit amounts also exhibit a granular reaction to natural disaster, the reaction of trade in goods is much more ambiguous.

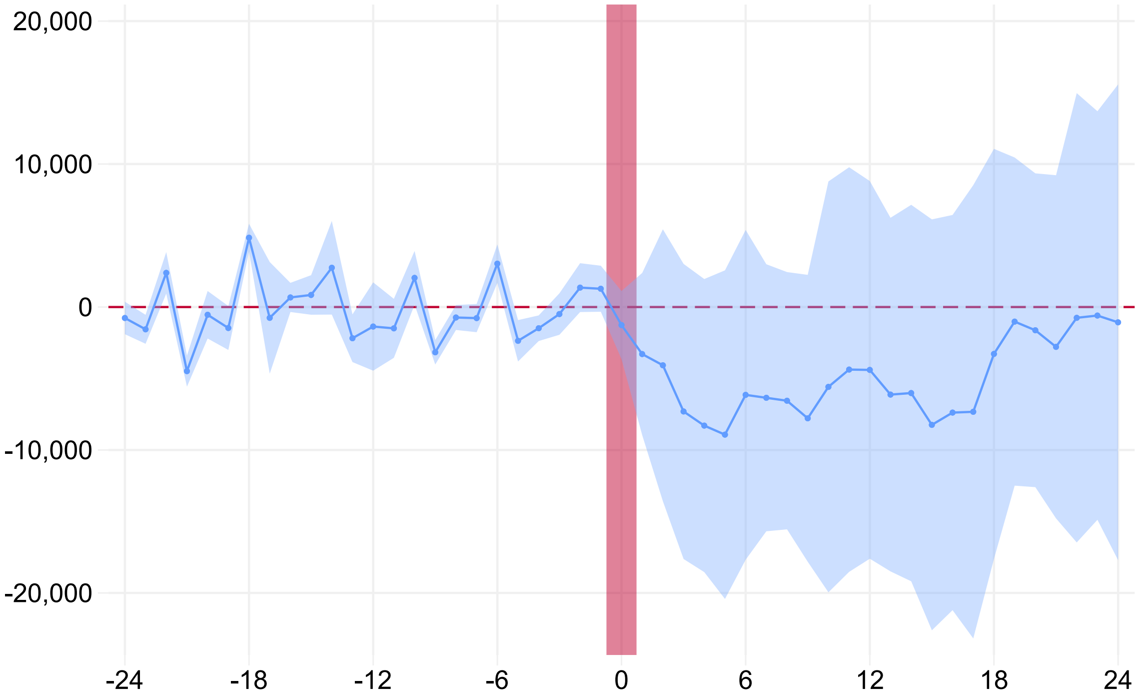
## 4.1 Quantities exported recover

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 foreign firms sourcing from French suppliers. Indeed 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 effect on actual cross-border flows 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 exporters of goods. We estimate the effect on the total value in euros exported by French suppliers to their affected destinations[8]. We report the result in Figure 11. 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 or 4.9% of the sample mean) and noisy. It decreases until 15 months after the disaster, without being fully significant at 1%. It likely reflects strong heterogeneity across firms in the response. It then recover around the 24*th* month.

We see from this exercise that trade credit amounts are more clearly affected by the disaster than overall export flows, which display a noisy and limited response to the disaster. Natural

[8]See Appendix C.1 for the effect on quantities, number of products and the unit values

**Figure 11:** Effects of Natural Disasters on the Export of Goods (Total Transaction Value in Euros)




Note: These figures present estimates of the coefficient $DID_k$ associated with natural disaster events from estimating Equation 4. The outcome variable is the three-month rolling average total value in euros exported by French suppliers to each of their destination. 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 a blue area. 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. Sub-sample of firms present in both French customs and Coface datasets (2010 to 2018). See Appendix D.3 for the details on the computations of this variable.

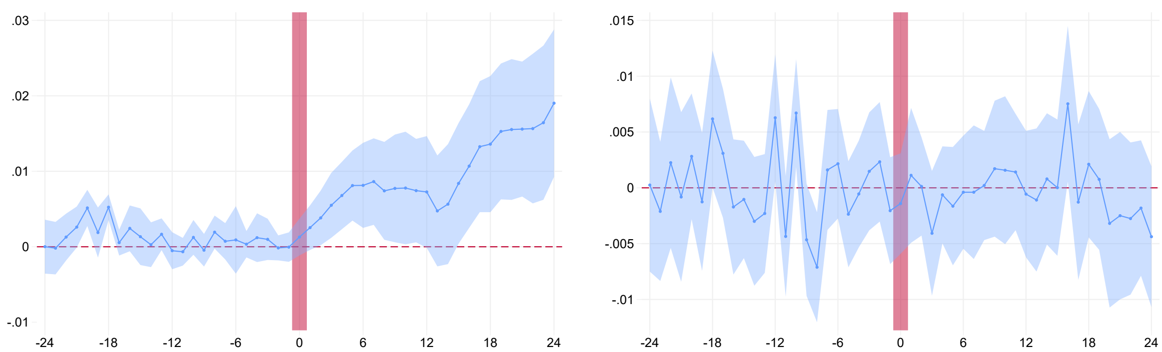
disasters are likely to weigh on the outlook in affected destinations mostly through changes in trade networks and trade financing structure (from trade credit to cash in advance), rather than through changes in aggregate trade levels. While the direct effect on overall trade flows is limited, the lower size of the trusted network of buyers to whom the supplier will extend trade credit is still likely to generate negative indirect effects in the economy by disrupting one of the primary sources of financing for importing firms. 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 may create financial disruptions along the supply chain.

## 4.2 The network shrinks but does not disintegrate

We estimate the effect of disasters on the probability to export under insured trade credit terms. We find a slightly positive effect, with a 2-percentage points increase in the probability to export under insured trade credit terms after 24 months (Figure 12a). This increased probability is however absent from customs' trade in goods data (Figure 12b). So this is not driven by firms starting to export goods into affected destinations. We interpret this difference between trade credit and trade in goods as an increase in demand for trade credit from at least some clients. This translates into a higher probability of having a few insured buyers among the incumbent clients in the affected destination. But this increase does not lead to a higher number of buyers (see Section 3.1).

**Figure 12:** Effects of Natural Disasters on the Extensive Margin

**(a)** Probability of Export under Insured TC Terms **(b)** Probability of Good Export - Any financing




Note: These figures present estimates of the coefficient $DID_k$ associated with natural disaster events from estimating Equation 4. In Panel 12a, the outcome variable is a dummy indicating whether the supplier has at least one trade credit relationship in a given destination. In Panel 12b, the outcome variable is a dummy indicating whether the supplier has exported any quantity according to customs data in a given destination (sub-sample of goods exporters only). 99% error bands, computed with robust standard errors clustered at the region-sector level, are displayed as a blue area. 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. Results are displayed including a supplier-time and sector-region-time fixed effects. See Appendix D.3 for the details on the computations of the outcome variables.

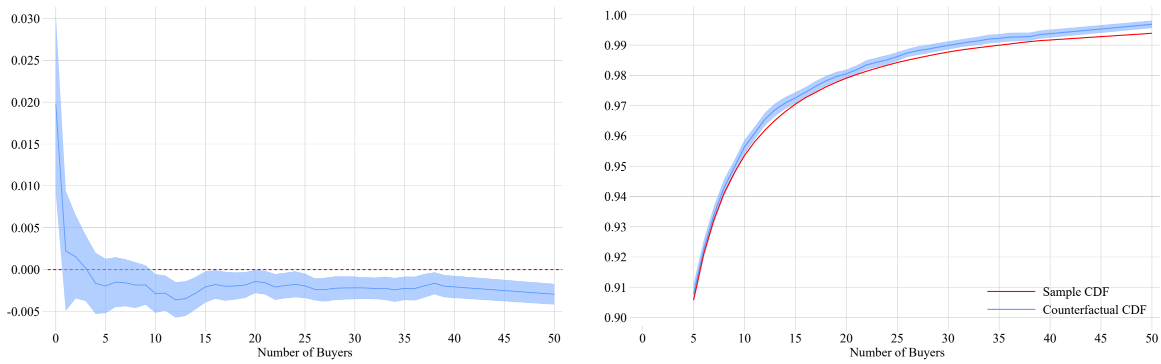
We know that the buyer margin is driving the negative effects of disasters while the country margin (i.e. the probability to have one or more buyers in the affected destination) exhibited small but positive effects. To further disentangle the extensive margin adjustment to external shocks, we estimate 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-destination pairs with a number of buyers greater than $x$. We repeat this estimation for every possible value of $x$ between 0 and 50 (the $99.5^{th}$ percentile) in increments of 1 buyer. 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).[9]

Figure 13a plots the effect on the distribution along the values of the outcome variable, here the number of buyers. We see that the negative effect on the number of buyers is largely explained by a decrease in the probability of having 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 as in Figure 12b). 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. 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-destination includes a lower number of suppliers with a lot of buyers. We show the sample CDF and its post-disaster counterfactual in Figure 13b. We see that suppliers at the $99^{th}$ percentile had 35 buyers before a disaster and only 30 two years later. Suppliers with a single foothold did not lose it and suppliers with a small local buyer base went mostly unaffected. At the same time, we observe a slight but noisy increase of average trade credit per clients (see Figure 5b). While the post-disaster network is smaller, it is also somewhat denser.

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

**Figure 13:** 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. The outcome variable is a dummy indicating a greater than $x$ number of buyers in the destination. In Panel 13a, we plot the sequence of coefficients from estimating the baseline equation for every value of $x$. In Panel 13b, we plot the observed CDF in red and the estimated counterfactual CDF in blue. The plot is truncated at 5 and 50 buyers for clarity. See Figure 31b for the full graph. For details on distribution regressions see Chernozhukov et al. (2013). 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 a blue area. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2008 and 2020, we consider only the largest one.

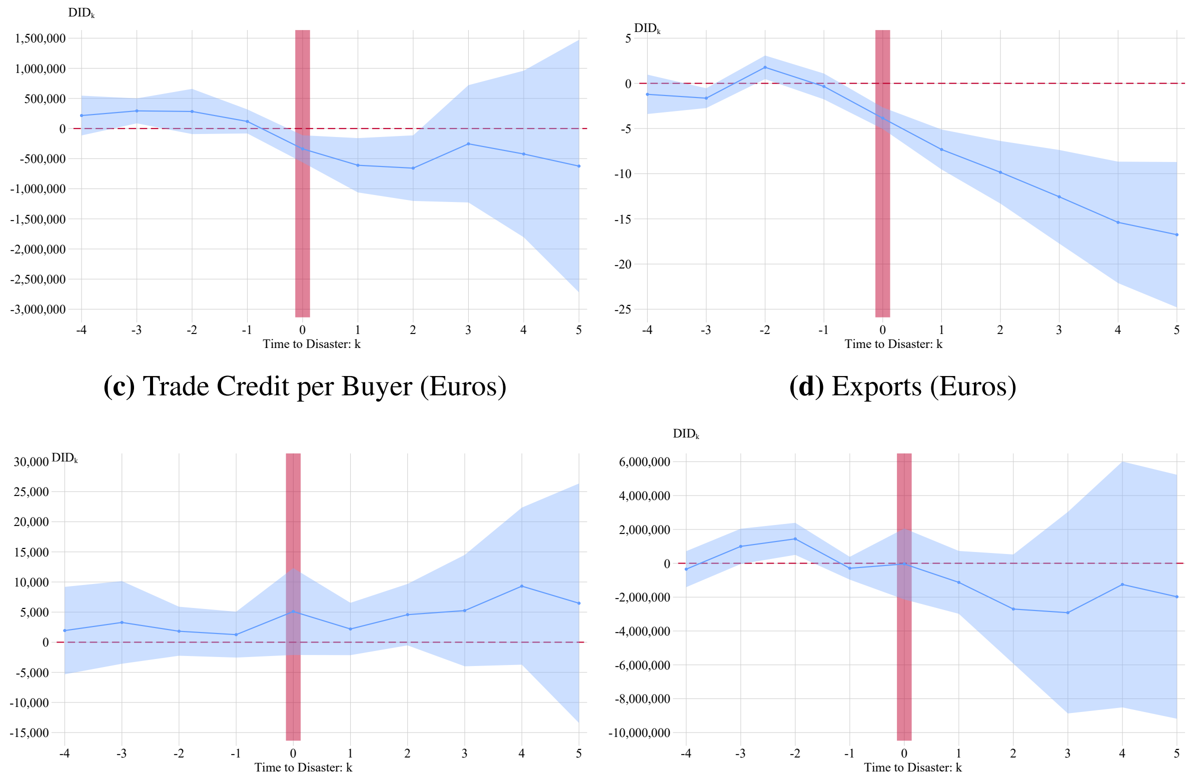
## 4.3 Suppliers' reallocation of trade

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. Since large, presumably multi-country, suppliers drive the response at the supplier-country level, they could either decrease their overall trade in the same proportion or absorb some of the shock by diverting their trade flows toward their clients in other 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 4. 99% error bands, computed with robust standard errors clustered at the sector level, are displayed as a blue area. 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 14c, the outcome variable is the average trade credit per buyer. In Panel 14d, the outcome variable is total value of exports. See Appendix D.3 for the details on the computations of those variables.

We highlight two key results. First, trade credit amounts experience only a temporary drop while the number of buyers under trade credit terms declines persistently, respectively by 646,941 EUR (Panel 14a, 10.4% of the average exposure per supplier in the sample) and 7.8 buyers (Panel 14b, 12.9% of the average number of buyers per supplier in the sample) after two years.[10] After 5 year, trade credit exposure has not declined any further while the number of

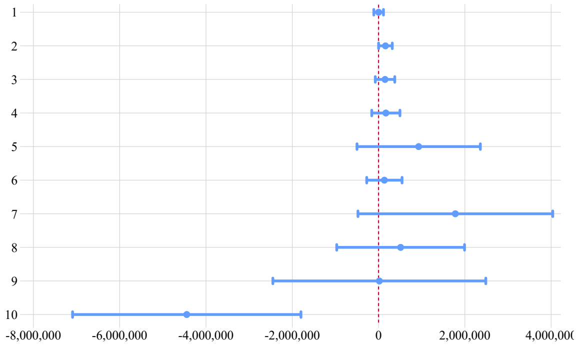
[10]Because of the differences in the event definition, here we consider only disasters in countries representing at least 10% of the supplier's trade credit exposure, the estimates are not directly comparable to the destination level results in Section 3.1

buyers under trade credit terms has continued to fall by an extra 16.7 buyers (-27.5% from the sample average). This means that suppliers do not compensate globally for the buyers they lost in affected destinations. The difference between the effect on the amount of trade credit and the number of buyers leads to a small but noisy increase in the average trade credit per buyer as visible on Panel 14c. Second, exports again experience a small and noisy drop: -14.8% (Panel 14d). It is worth noting that at the supplier level, they follow quite closely the pattern of trade credit sales (-10.4%). Our interpretation is that, following a disaster, suppliers rearrange their network of buyers globally without creating new trade credit partnerships.

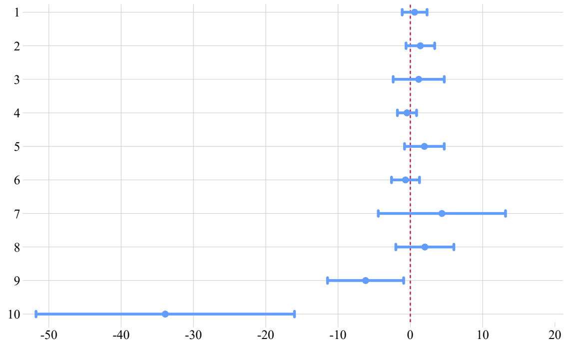
We now investigate whether this diversion effect is stronger for suppliers with a larger partner base globally. Intuitively, firms with many buyers in unaffected destinations should find it easier to compensate for the losses in the affected destination. Figure 15a and Figure 15b show that while the largest suppliers are the ones experiencing most of the effect in trade credit exposure, they do not display a significant response in the amount of goods they export (Figure 15c). The response of exports is noisy and likely reflects strong underlying 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 once again more sensitive than smaller exporting firms. At the same time they are also able to restructure their trade network by either deepening their relationship with existing buyers or widening their buyer base in other destinations under alternate financing terms (i.e. without using trade credits). While the data doesn't allow us to rule in favor of one or the other, we can at least test whether the quantity of goods exported per buyer does in fact increase after a disaster. We show the results in Figure 30. We observe that for those suppliers in the top decile of size the ratio of total exports per buyers increases after a disaster.

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

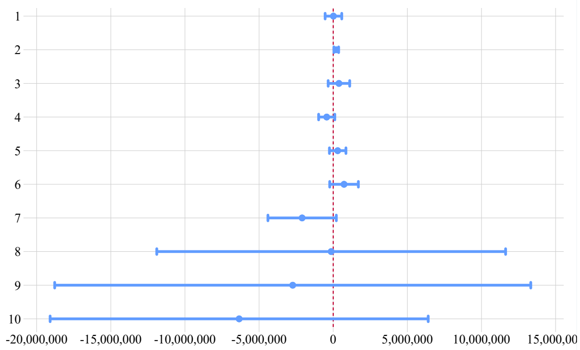
**(a)** Trade Credit (Euros)




**(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 4. 99% error bands, computed with robust standard errors clustered at the sector level, are displayed as a blue area. 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.3 for the details on the computations of those variables.

# 5 Mechanisms

Our results emphasize the importance of both the supplier and 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 buyer quality after a disaster (Figure 27). This decline is driven both by firm assessments being downgraded as well as firms with a good assessment leaving the production network of the French supplier (Figure 10). "Marginal firms" with a very low assessment 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 28). 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 suppliers of non specific outputs (Figure 9) 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 of the relationship 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.

# 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 driven by lower trade credit amounts from suppliers 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 assessment 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 partners at a low cost.

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# APPENDIX

## A The effect is not due to misspecification in the event definition

We check the robustness of our results to the definition of our event variable. We first look at a possible contamination of our worst disaster variable by other events in appendix A.1. We confirm the absence of contamination for our event variable. We then check our results using two alternative specifications of the event in appendices A.2 & A.3: the first big disasters and the worst disasters, defined as greater than the third quartile instead of the median. Our results are essentially unaffected.

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

**Figure 16:** Timing of selected events

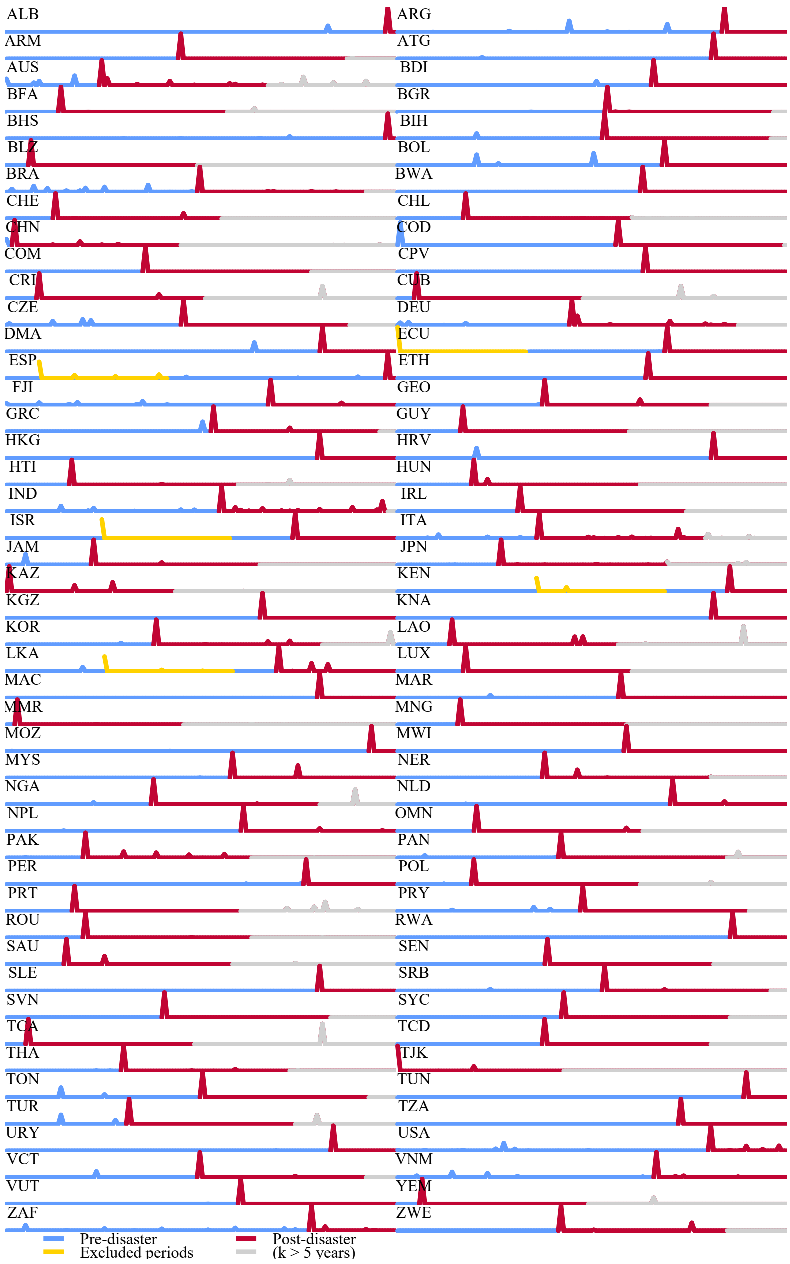
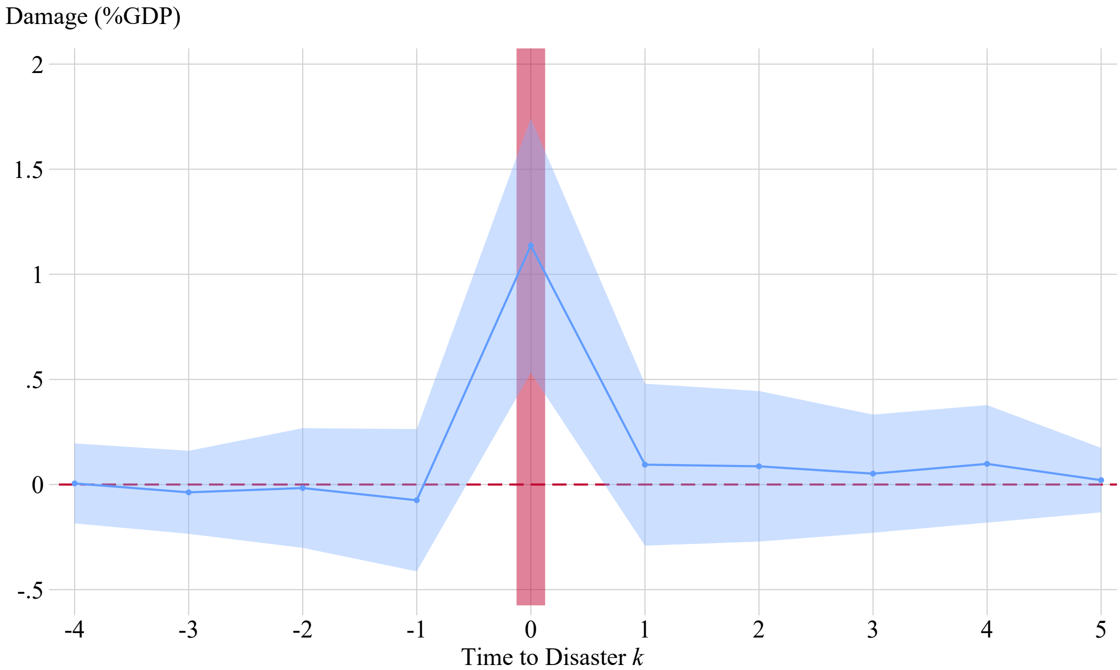


**Figure 17:** Natural Disasters and Damages



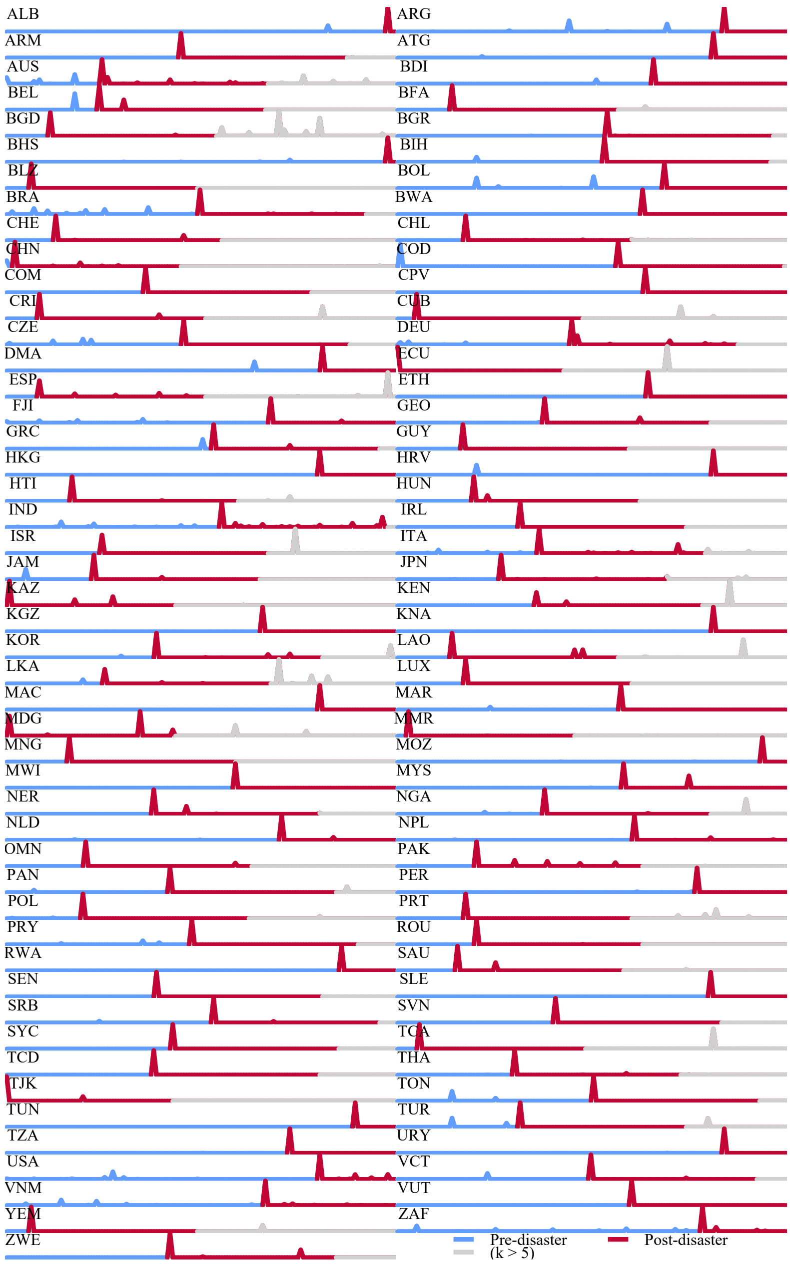

Note: These Figure presents the response function of estimated damage in percentage of GDP around a natural disaster with our baseline definition. The estimated equation is $D_{j,t} = \sum_k \beta_k + \gamma_j + \gamma_t + \epsilon_{j,t}$

## A.2 Alternative definition: 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. We graph the timeline of events with this new definition in Figure 18. We present the results of the DiD analysis at the yearly level with this definition of event in figures 19a & 19b. We also test for the validity of our control group by conducting an estimation excluding the never treated in Figure 20. We obtain in both cases very similar results.

### A.2.1 Timing for the first big disasters

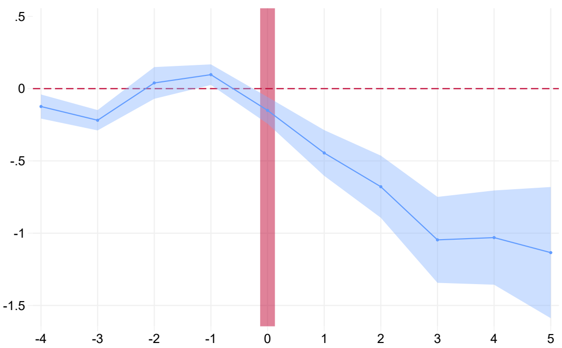
**Figure 18:** Timing of first big disasters



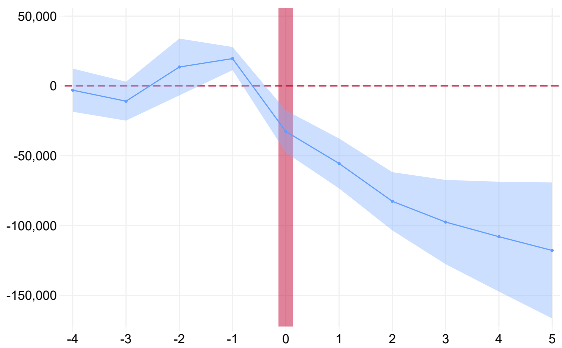
### A.2.2 Main results with first big disasters

**Figure 19:** Effect of Natural Disasters on the Number of Buyers - First big disaster

**(a)** Number of buyers




**(b)** Trade credit amount



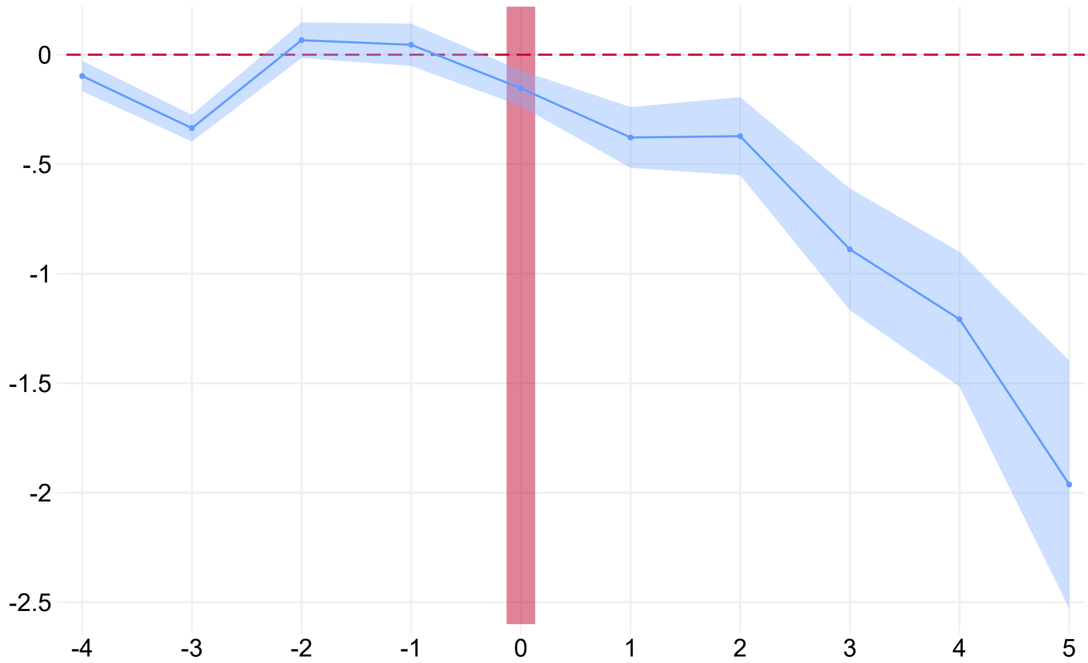

Note: These figures present estimates of the coefficient $DID_k$ associated with natural disaster events from estimating Equation 4 at the yearly level. We include here a supplier-time and a region-sector-time fixed effects. 99% error bands, computed with robust standard errors clustered at the firm-time 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.2.3 Main results for first big disaster, excluding the never treated

## A.3 Alternative definition: Worst disasters in the last quartile

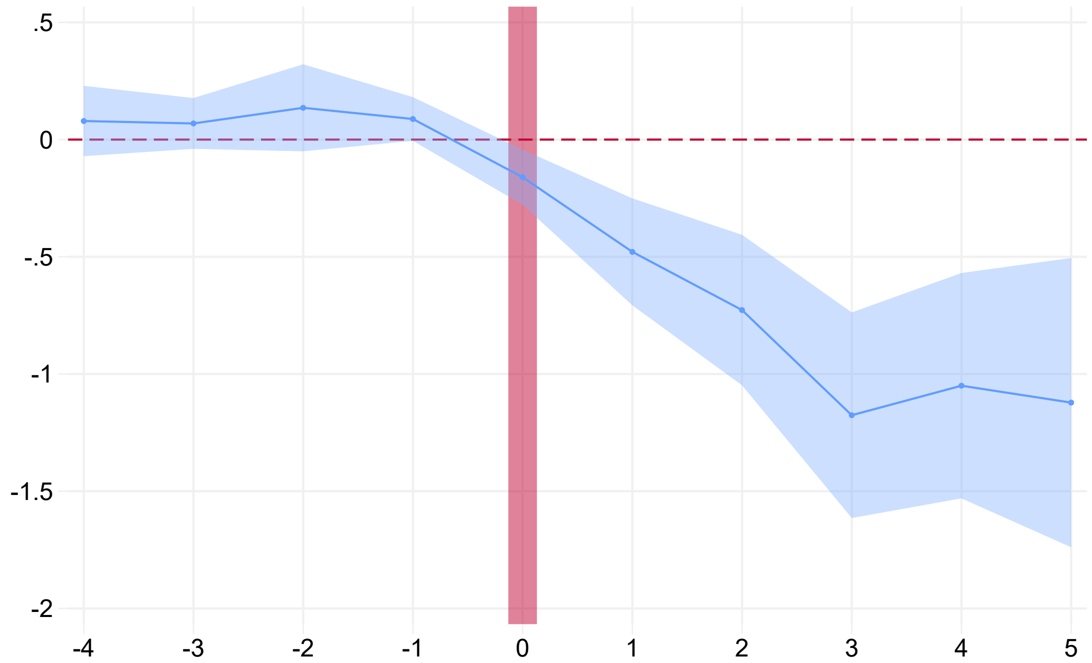
As a last check on our definition of events, we take the worst event in the country but change the threshold for the event to be selected. We select a disaster such that it causes damages relative to GDP greater than the third quartile in the whole sample, and such that it is the worst event in the country. We mark as missing any observation polluted with events reaching 50% of the damages caused by this event. We present the results of the analysis at the yearly level on Figure 21. We see that the effect is very comparable and even slightly bigger than what we observe with the other definitions presented above.

**Figure 20:** 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 4 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 a blue area. The outcome variable is the the number of buyers purchasing from the supplier at credit in each destination country. See Appendix D.3 for the details on the computations of this variable.

**Figure 21:** Effect of Natural Disasters on the Number of Buyers - Top quartile events



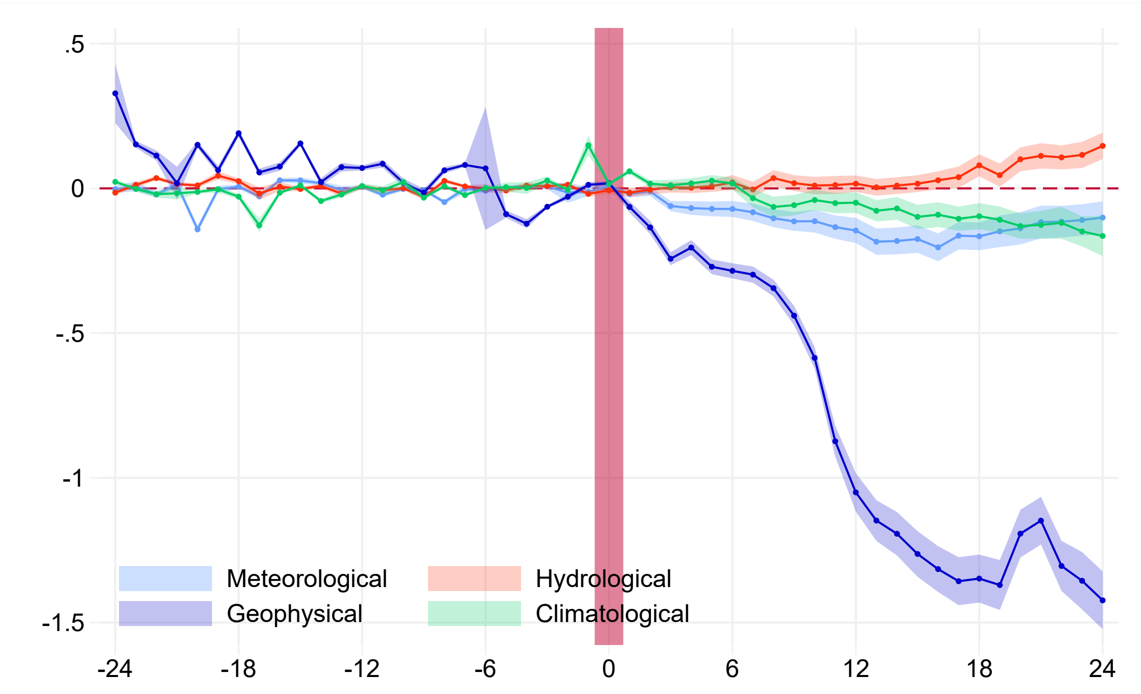

Note: These figures present estimates of the coefficient $DID_k$ associated with natural disaster events from estimating Equation 4 at the yearly level. We include here supplier-time and region-sector-time fixed effects. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as a blue area. 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.3 for the details on the computations of this variable.

# B Heterogeneity and granularity in the effect: Robustness tests

## B.1 Heterogeneity in types of disasters

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 22. 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 22:** Heterogeneity in Types of Disasters



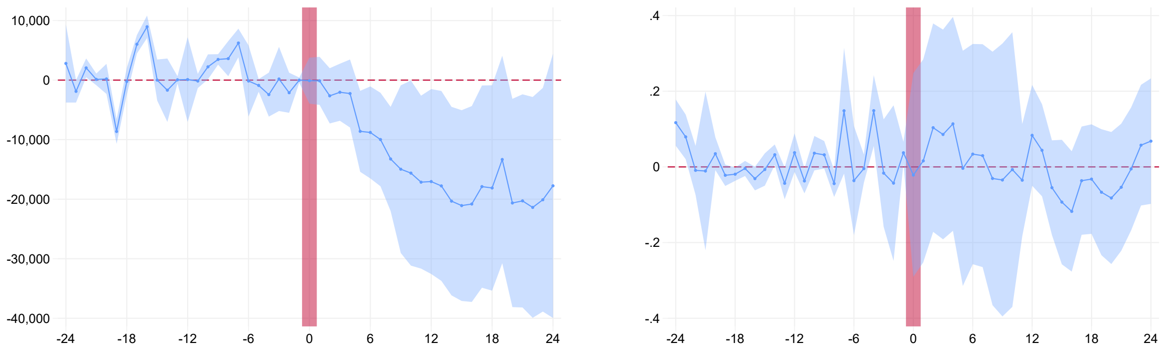

Note: These figures present estimates of the coefficient $DID_k$ associated with natural disaster events from estimating Equation 4. We include here a supplier-time and a region-sector-time fixed effects. 99% error bands, computed with robust standard errors clustered at the firm-time level, are displayed 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.

## B.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 23a, 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 23b). We find no significant effect. This indicates that the effect reflects a change in demand for insurance by the supplier rather than a change in supply by the insurer.

**Figure 23:** Supplier vs. Insurer Effect

**(a)** Effect on Requested Amount **(b)** Effect on Obtained/Requested Ratio

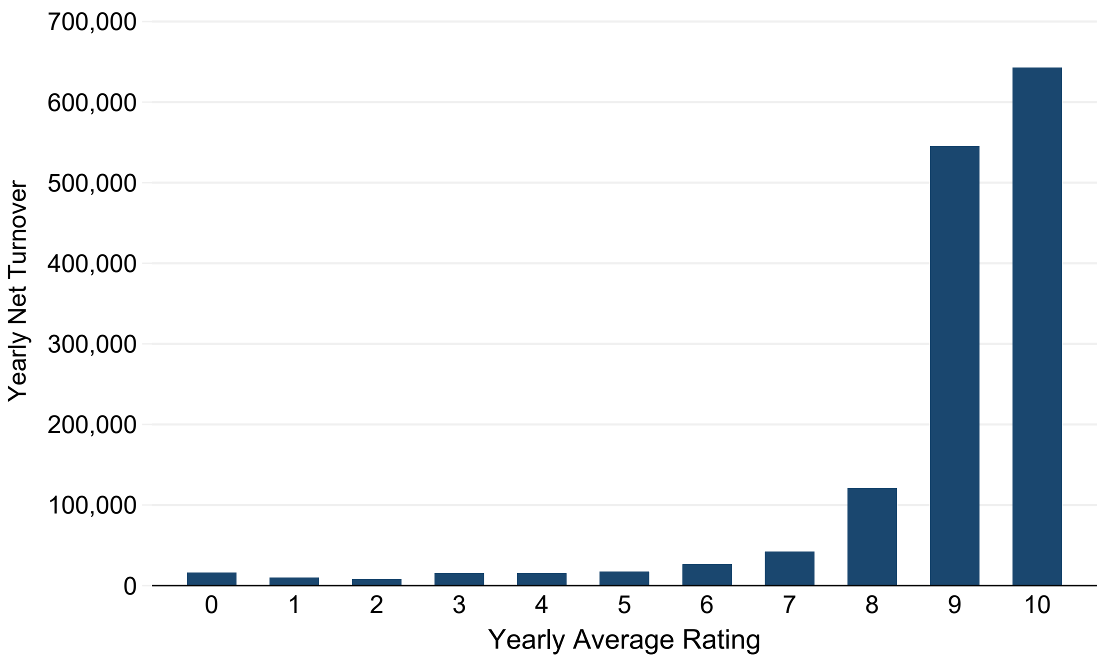



Note: These figures present estimates of the coefficient $DID_k$ associated with natural disaster events from estimating Equation 4. We include supplier-time and region-sector-time fixed effects. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as a blue area. 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 23a the requested amount of trade credit guarantee requested by the supplier and in Panel 23b the ratio of obtained trade credit guarantee over requested. See Appendix D.3 for the details on the computations of all LHS variables.

## B.3 Buyers' assessment and size

In order to further characterize the response on the buyer side, we look at the correlation between assessments and turnover taking the examples of French buyers (not used in the analysis) for which we have both types of data. Using FIBEN fiscal data, we look at the average yearly net turnover of the French buyers present in the Coface database for each assessment category during our sample period. We see in Figure 24 that the highest categories are made of much larger firms on average. Even though we do not have the data to verify this correlation in other countries, Coface methodology remains the same across countries. Therefore, we can infer from the French examples that highest-rated buyers are the biggest in terms of net turnover.

**Figure 24:** Positive Correlation Between Assessment and Turnover

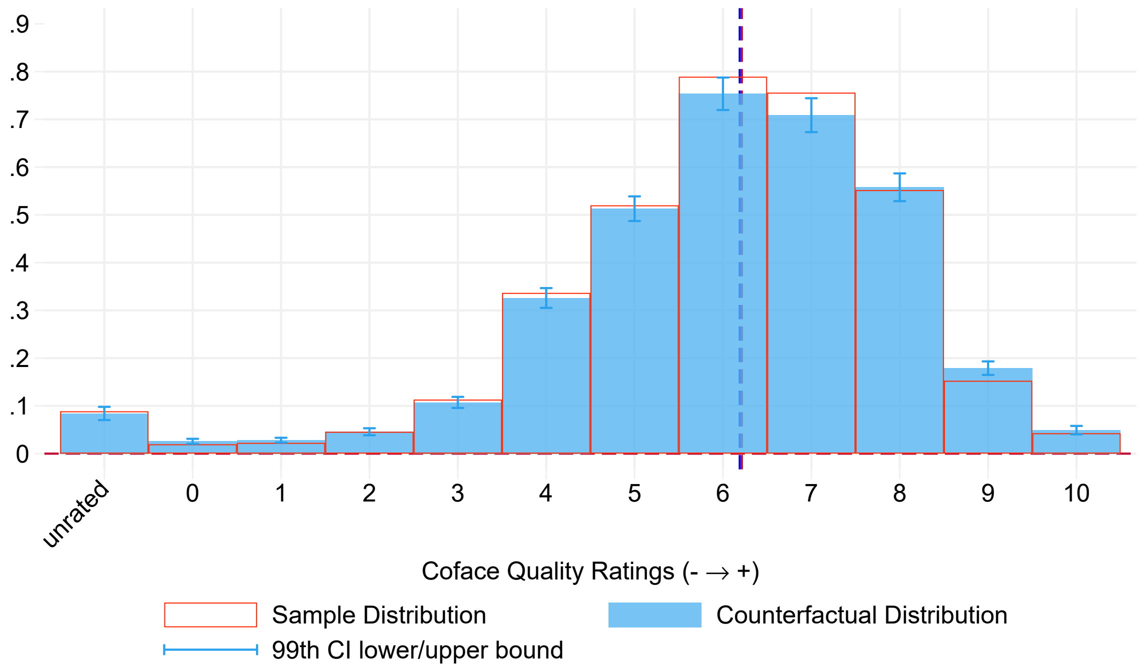



Note: This shows the average yearly net turnover of firms in each assessment categories for French buyers using Coface assessments and FIBEN data. The y-axis corresponds to amount in thousands EUR.

## B.4 Absence of anticipatory effects per assessments 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 3.3 by estimating the effect on the number of buyers per supplier in each assessment category in the two years prior to the disaster. We find no overall meaningful decrease in buyer quality prior to the disaster as shown in Figure 25. We provide the full dynamic response of each assessment category in Figure 26.

**Figure 25:** Effect of Natural Disasters on Buyer Quality 2 Years prior to the disaster

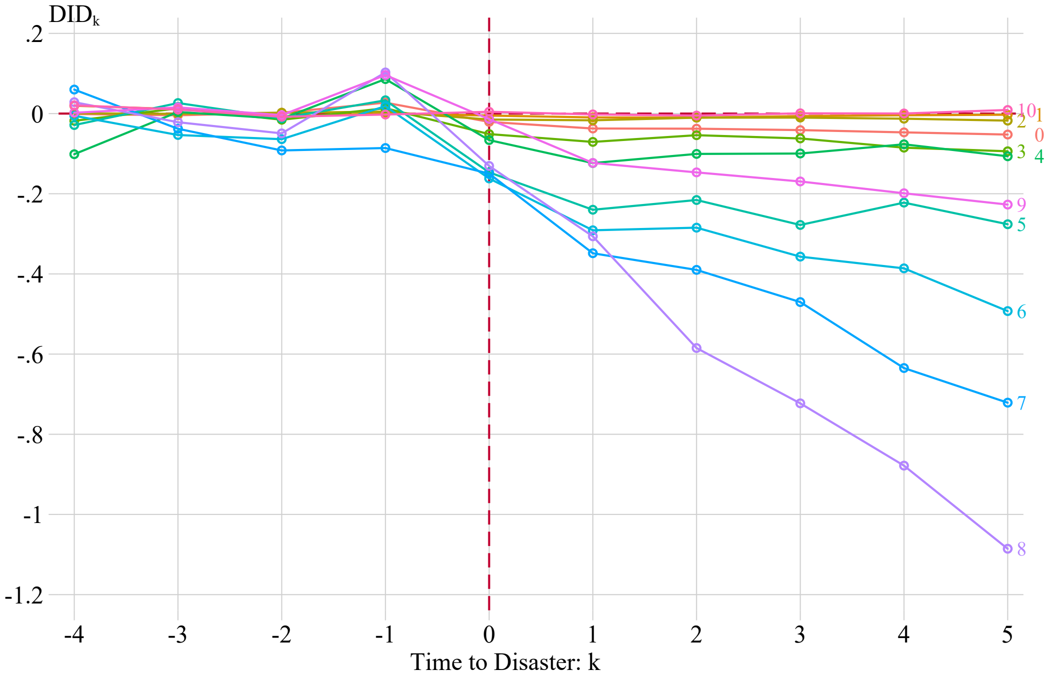



Note: These figures present estimates of the coefficient $DID_{k=-2}$ associated with natural disaster events from estimating Equation 4. We include supplier-time and region-sector-time fixed effects. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as 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 assessment category. We plot the sample distribution of assessments in red and its counterfactual distribution in blue.

## B.5 Effect on overall quality

We compute the number of buyers in each assessment category at each period after the disaster: $T^r_{j,f,t} = \sum \mathbf{1}(TC_{j,b,f,t} > 0 \cup R_{b,t} = r)$. We estimate the effect of natural disasters on the number of buyers per supplier in each assessment 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. This time we do not freeze the assessments as in 3.3 but look at the effect of natural disasters on the number of buyers per supplier in each category k periods after the disaster. 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 27. The bins in red represent

**Figure 26:** Effect of Natural Disasters per ex-ante assessment category

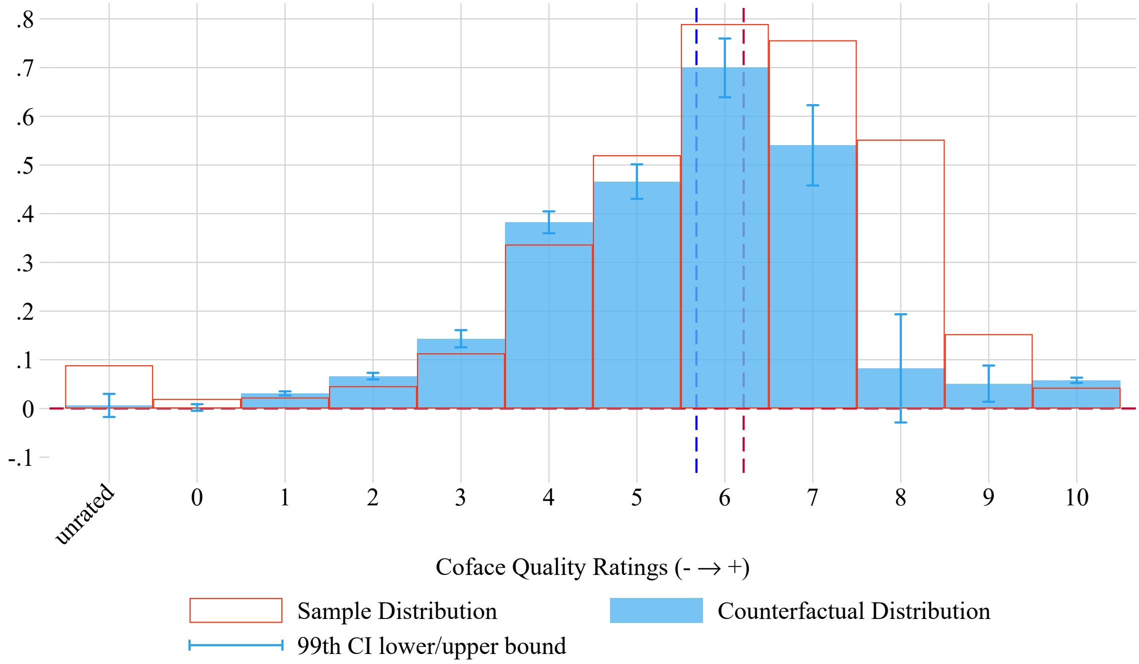



Note: These figures present estimates of the coefficient $DID_k$ associated with natural disaster events from estimating Equation 4. Each line represent a different assessment category. We include here supplier-time and region-sector-time fixed effects. Error bands are omitted for clarity. Events are 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.3 for the details on the computations of this variable.

the sample average number of buyers in each assessment 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 assessments has shifted toward the left, i.e. it has worsened. In particular, there is a much lower number of suppliers in assessments 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 is a combination of "treatment effect" i.e. buyers are being downgraded or "composition effect" i.e. good buyers disappears from the suppliers network.

**Figure 27:** Effect of Natural Disasters on Buyer Quality after 2 Years



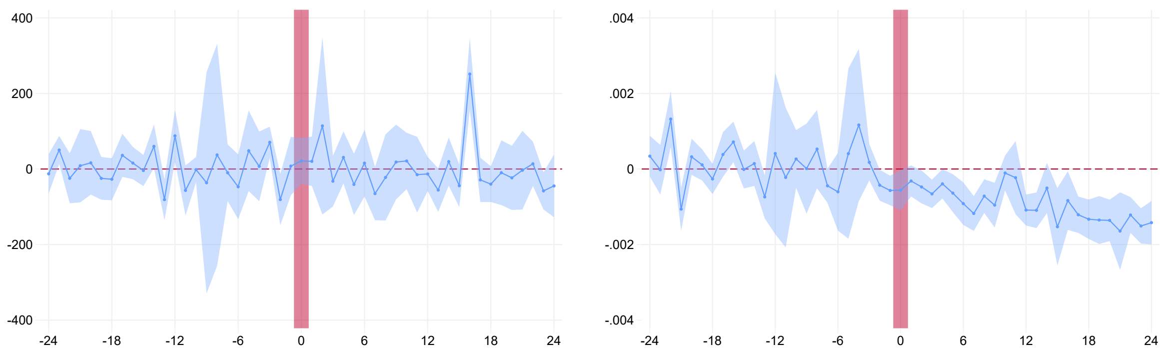

Note: These figures present estimates of the coefficient $DID_k$ associated with natural disaster events from estimating Equation 4. We include here supplier-time and region-sector-time fixed effects. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue 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 assessment category. We plot the sample distribution of assessments in red and its counterfactual distribution in blue.

## B.6 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 present the results in Figure 28, with the amount of defaults in Figure 28a and the number of defaults in 28b. 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 28:** 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 a blue area. 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 28a, the outcome variable is the amount of default on trade credit. In Panel 28b, the outcome variable is the number of defaults. See Appendix D.3 for the details on the computations of those variables.

# C Reallocation and supplier-level net effect: robustness tests

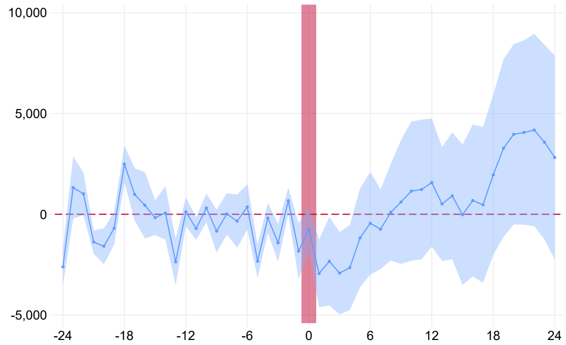
## C.1 Trade in goods and natural disasters

In section 4.1, we use customs data on trade in goods to investigate whether there are any effect of natural disasters on actual cross-border volume of trade in goods. In this appendix section, we 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 results in Figure 29. In Panel 29a, we see a small and short-term decline in the quantity exported before a medium-run increase albeit a non-significant one. The same non-significant increase is visible for unit values in Panel 29b. Finally, Panel 29c indicates that natural disasters do not lead to a lower number of exported products.

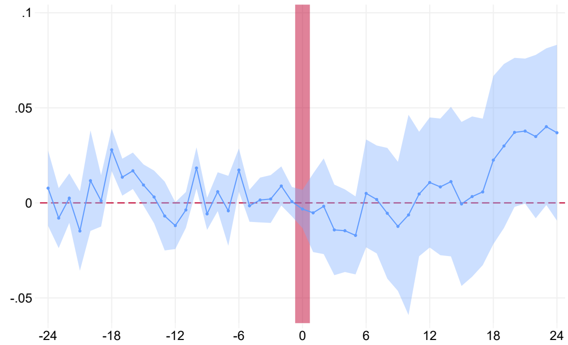
In Figure 30 we conduct the estimation of Equation 4 at yearly level looking at the amount exported per trade-credit buyer- i.e. buyer using trade credit- over two sub-samples. We sep-

**Figure 29:** Effects of Natural Disasters on the Export of Goods

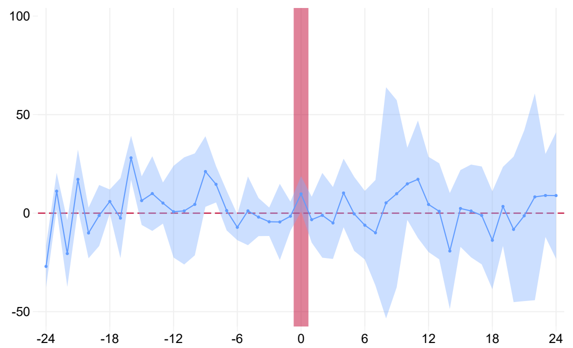
**(a)** Total Transaction Quantity (Kg)




**(b)** Unit Value (Euros/Kg)




**(c)** Number of Products (HS6)



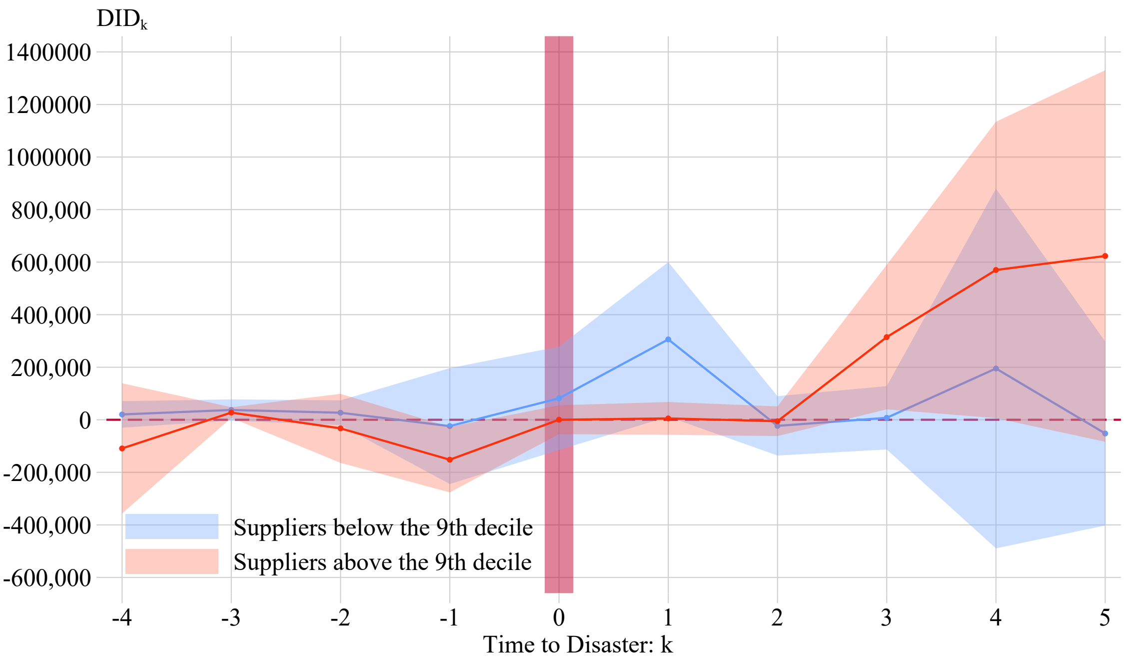

Note: These figures present estimates of the coefficient $DID_k$ associated with natural disaster events from estimating Equation 4. We include here supplier-time and sector-region-time fixed effects. 99% error bands, computed with robust standard errors clustered at the region-sector level, are displayed as a blue area. 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 29a, the outcome variable is the three-month rolling average quantity exported in kilograms. In Panel 29b, the outcome variable is the three-month rolling average unit values (euros per kilogram) of the exports. In Panel 29c, 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.3 for the details on the computations of those variables.

arate the sample between suppliers below and above the ninth decile of size measured by the supplier's global trade credit amount.

## C.2 Effects on the CDF

## C.3 Larger response for larger suppliers

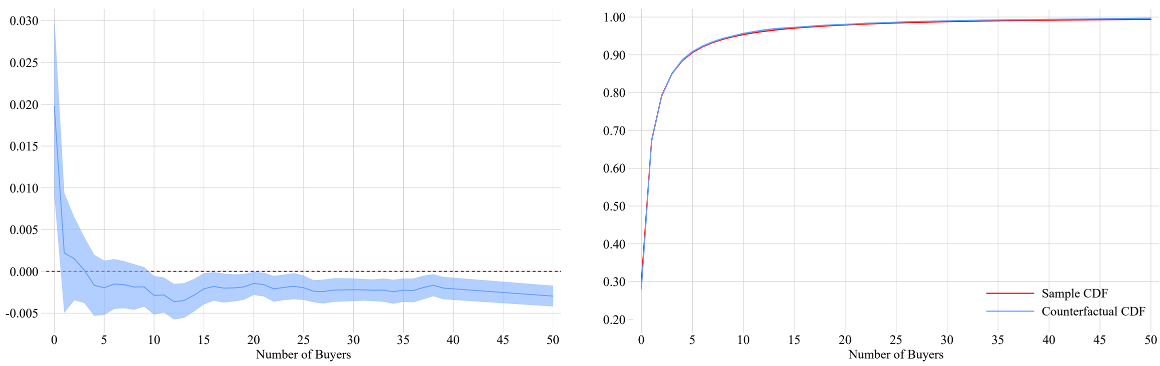
**Figure 30:** Effect of natural disasters on exports per buyer for suppliers below and above the $9^{th}$ decile




Note: These figures present estimates of the coefficient $DID_k$ associated with natural disaster events from estimating Equation 4. The outcome variable is the total value of exported goods divided by the number of trade credit buyers. 99% error bands, computed with robust standard errors clustered at the sector level, are displayed as a blue area. 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. Sub-sample of firms present in both French customs and Coface datasets (2010 to 2018). See Appendix D.3 for the details on the computations of this variable.

**Figure 31:** Effect of Natural Disaster on the Distribution of Buyers per Supplier-Destination

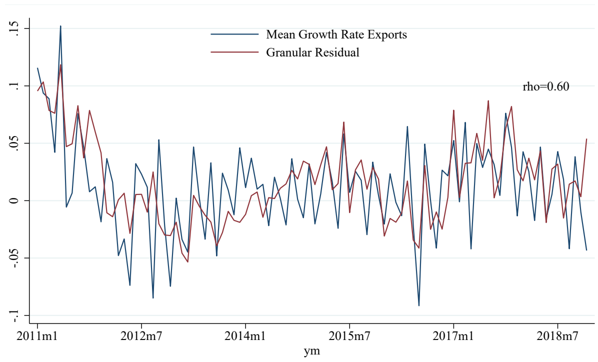
**(a)** Distribution Regressions **(b)** Counterfactual CDF



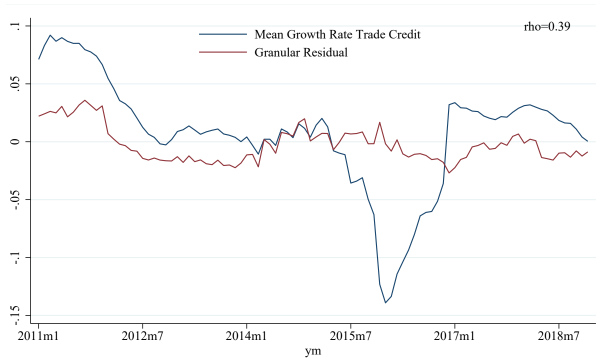

Note: These figures present estimates of the coefficients $DID_k$ associated with natural disaster events from estimating Equation 4. The outcome variable is the number of buyers per supplier-destination. We include here supplier-time and region-sector-time fixed effects. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as a blue area. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2008 and 2020, we consider only the largest one. In Panel 31a, we plot the sequence of coefficients from estimating the baseline equation for every value of $x$. In Panel 31b, we plot the observed CDF in red and the estimated counterfactual CDF in blue. For details on distribution regressions see Chernozhukov et al. (2013).

**Figure 32:** Average growth rate and granular residual

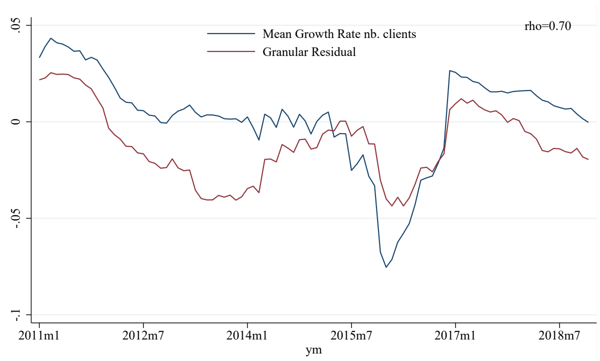
**(a)** Trade in goods




**(b)** Trade credit amount




**(c)** Number of buyers under trade credit




Note: These figures present the average growth rate and the granular residual as computed by Bricongne et al. (2022) for each variable of interest. The growth rate is computed as the Davis-Haltiwanger growth rate: $Y_t = \frac{Y_t - Y_{t-1}}{0.5 \times (Y_t + Y_{t-1})}$.

# D Miscellaneous

## D.1 Disaster Types - Definitions

**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

## D.2 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.3 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 assessment $R = r$. (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)

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

- "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)

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

## D.4 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.

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