Trade Networks and Natural Disasters

Timothee Gigout[*] Mélina London[†]

March 4, 2021

Preliminary

Abstract

We study how international trade networks react to large natural disasters. We combine exhaustive firm-to-firm trade credit and disaster data and use a dynamic differences-in-differences identification strategy to establish the causal effect of natural disasters on the size, shape and quality of international trade networks. We find strong and permanent negative effects on the exports and trade credit sales of French suppliers. This effect operates exclusively through the number of buyers. It is concentrated among suppliers with few buyers in the affected destination. Additionally, disasters induce a negative shift in the distribution of the quality of buyers.

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

Keywords: Firm Dynamics; Trade Networks; Natural Disaster.

Acknowledgement: We thank participants in the INSEAD-CdF brownbag seminar.

[*]Collège de France, Email: timothee.gigout.magiorani@gmail.com.

[†]Coface - AMSE (Aix-Marseille University), Email: melina.london@coface.com.

1 Introduction

Cross-border buyer-supplier relationships represent a costly investment by both parties. The more suppliers tailor their product for a specific client, the higher the sunk cost. Disruptions to those international trade linkages carry a high economic cost. Natural disasters are a recurring and increasing source of destruction of physical capital and durable consumption goods. If natural disasters disrupt international buyer-supplier relationships, the economic recovery in the affected country will take longer and be more costly. The shock will also propagate across borders through global value chains. There is a gap in the literature on the resilience of trade networks to natural disasters. In this paper, we study how natural disasters affect characteristics of international trade networks.

A natural disaster will affect international trade networks mainly through a combination of direct damage to the country production apparatus and through damage to the country transport infrastructure. Those will lead to lower productivity in the affected destination and rising trade costs with the rest of the world. Standard models of trade with supplier heterogeneity (Melitz, 2003) or buyer heterogeneity (Antras et al., 2017) or both (Bernard et al., 2018) can yield a few basic predictions. The combination of increased trade costs and decreased efficiency should lead to an overall lower number of matches with the destination country. This effect would operate both through a lower number of suppliers reaching the affected country and buyers sourcing from France. The effect on the quality of the network is more ambiguous. A higher trade cost faced by affected buyers should lead to a higher selection effect and therefore a higher quality of "surviving importers". The negative productivity shock among all potential buyers should lead to a lower quality among incumbent buyers.

To test those theoretical hypotheses, we use novel firm-to-firm trade credit data from one of the top three international credit insurers (Coface). We pair it with exhaustive disaster data from EM-DAT. We then estimate the causal effect of natural disasters on various firm-level outcomes describing the size, shape and quality of international trade networks using a dynamic differences-in-differences identification strategy. We use the de Chaisemartin and d'Haultfoeuille (2020) estimator and provide an estimate that is robust to heterogeneous treatment effects. Within that framework, we control for either supplier-period shocks or geographical region-sector-period shocks. In the first case, identification results from the supplier exporting to at least two different countries, one of which is hit by a disaster at some point. In the second case, identification comes comparing several suppliers operating in the same sector but exporting to different countries within the same region, where at least one will be affected by a disaster.

We find evidence of large and persistent disruptions to international buyer-supplier relationships. Suppliers decrease their trade credit exposure to affected countries in similar proportion to the observed fall in total exports. After just two years, the level of exports has fallen by 5.61% or €11,300 (from an average €202,500). The losses in trade credit exposure increase from about €17,000 after 12 months to €29,600 24 months later (from an average exposure of €256,000). This represents a 11.58% decline, confirming the absence of reversion towards other types of financing once exports are done under trade credit terms. Suppliers reduce their trade credit exposure mostly through the extensive margin by reducing their number of clients rather than exposure per client. The number of clients decrease by 7.22% or 0.18 buyers after 24 months (from an average of 2.49 buyers per country-supplier pair). This fall in the number of buyers is persistent, their number decreasing by about 0.85 after five years. Suppliers with few buyers (between 2 and 10) experience the greatest losses even though we observe negative effect on the rest of the upper part of the distribution (10 to 50+). Lower losses among bigger suppliers is consistent with a financial constraint mechanism. Suppliers with more buyers are likely to be bigger and thus less financially constrained and more inclined to continue to support the risk of providing credits to their buyers in a depressed environment. We also observe that this fall in the number of partners in the affected countries translate in a decrease in the average quality of remaining ones. When differentiating across ratings at the time of the disaster, we find that the fall is greater for buyers with a medium to high rating. Additionally disasters are not followed by a rise in insolvencies. In line with the greater impact on the bottom of the distribution of suppliers, we expect assortativity mechanisms to be key to explain such combination of results. Larger buyers, more financially sound, are matched with smaller buyers that will not be able to demonstrate solidarity in times of crisis compared to large suppliers matched with lower-rated firms. Thus, large buyers will have to reorganize their input sourcing to face the shock, likely diverting trade towards suppliers with lower trade costs than French exporters.

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. Boehm et al. (2019) shows that relationships between US affiliates and Japanese parent companies were mostly resilient to the 2011 Tohoku Earthquake. They show that the earthquake caused a significant drop in sales of Japanese firms to their US affiliates over the short term. This lead to major disruptions of production processes in the US, highlighting shock propagation through production linkages. However, they show this effect is only short-lived. It does not endanger the relationship between the firm and its affiliate over the long-term. In contrast with them, we find a persistent effect (beyond five years) of natural disasters. Foreign buyers and French suppliers included in our dataset are not locked in a relationship the same way US affiliates of Japanese firms are. This persistent effect would be consistent with a model of forced experimentation as in Porter (1991) [1]. Our work is closely related to Kashiwagi et al. (2018). They focus on the effect of Hurricane Sandy on the domestic and international production networks of US firms. They find short-run propagation limited to domestic supplier & customers without international transmission to their foreign counterparts. Barrot and Sauvagnat (2016) focus on US production networks but include data on all natural disasters occurring in the US between 1978 and 2013. They find the intensity of the downward propagation to be highly dependent on input specificity. The more specific the input, the harder it is to switch to another other source of input and the greater the consequences for the firm downward on the chain. 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. Our contribution relative to those studies is two-fold. First, we use data

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

on all large natural disasters between 2010 and 2020 rather than just two events in the US and Japan. Additionally, our data is not restricted to foreign affiliates or publicly traded firms. It covers a much more common type of cross-border linkages: goods sold under trade credit. Second, while they focus on how the network contributes to the propagation of the shock, we focus instead on how the network itself is affected by the shock.

This paper relates to the literature on the impact of large shocks on trade. 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. In this respect, it is different from the effects on the intensive margin of the Great Financial Crisis identified in Bricongne et al. (2012) or the effect of the adoption of broadband in France in Malgouyres et al. (2019).

Our study is related 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 and therefore has an impact on the productivity distribution of exporters. In a related study, Martin et al. (2020) finds that uncertainty reduces the rate of formation and separation of seller-buyer relationship, in particular for pairs trading stickier products.

Our work is also related to the literature on trade credits and the decisions of suppliers 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 solidarity. In a following paper, Garcia-Appendini and Montoriol-Garriga (2020) refine this idea and show that the increase in trade credit from suppliers to their distressed clients is strongly related to suppliers' switching costs to replace those clients. The harder the buyer is to replace, the longer the supplier will provide trade credit before bankruptcy. We also contribute to the literature on the economic effect of natural disasters (Noy (2009), Felbermayr & Groschl (2014). El Hadri et al. (2019) finds mixed evidence of a negative effect of natural disasters on product level exports from affected destinations.

The rest of the paper is organized as follows. Section 2 presents the data and details our empirical strategy and section 3 shows our baseline results. We conduct further robustness tests in section 4. Section 5 concludes.

2 Data and Methodology

We first describe our two main source of data in Section 2.1 and 2.1. Then we show some stylized facts from our estimation sample in Section 2.1. Finally, we present our empirical strategy in Section 2.2

2.1 Data

Trade Credit Data

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

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

Table 1: Sample Descriptive Statistics

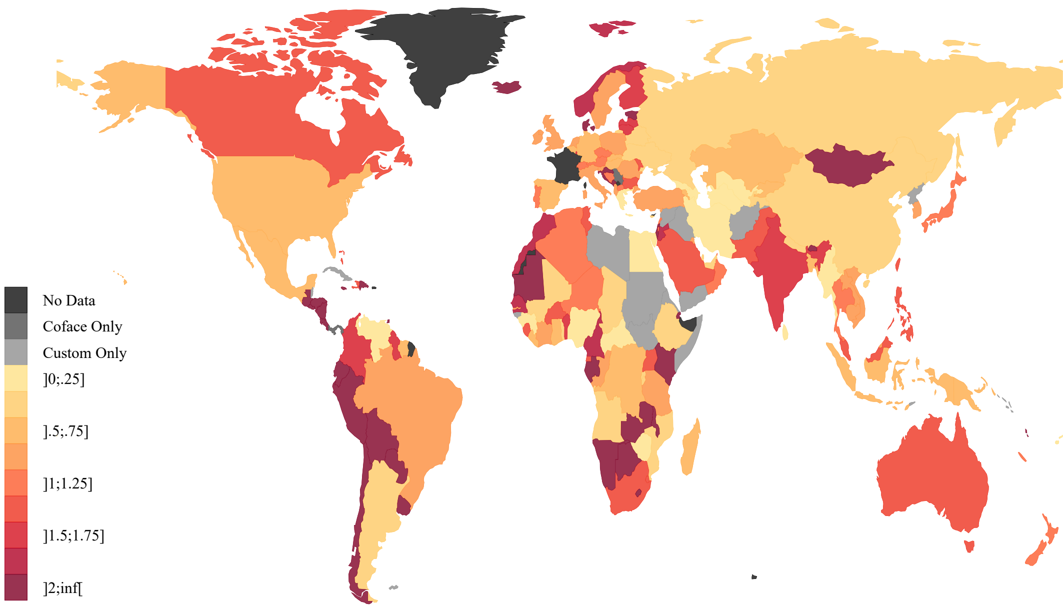
	N	Mean	Median	Std.Dev.
Panel A Supplier-Destination Coface				
Monthly Trade Credit (K EUR)	14,692,164	256.15	10	1929.33
Number of Debtors		2.49	1	13.51
Exposure per Debtor (K EUR)		108.15	50	702.44
Requested Amount (K EUR)		358.93	10	2820.94
Defaults (Number)	23,724	1.04	1	0.20
Amount of Defaults (K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

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

control for supplier-period fixed effects in our analysis.

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. [2] In the case of French exporters studied here, the number of firms in Coface database is equal to 16% of those in French custom data. Figure 1 shows the ratio of the amount of trade credit flows recorded in the database with flows recorded in French customs data for French exporters. Almost every country included in French custom data is included in Coface data. The few exceptions are Iran, Cuba, Sudan, Libya and Yemen. The orders of magnitude of trade credit and trade are similar across the two databases.

Figure 1: Trade Credit to Customs Data Coverage



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

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

Disaster Data

For natural disasters, we use the exhaustive EM-DAT database from the Center for Research on the Epidemiology of Disasters (CRED)[3]. 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 and estimated damages in US$. We use data from January 2008 to December 2019.

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

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

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

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

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

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

Table 2: Natural Disasters (2008-2019)

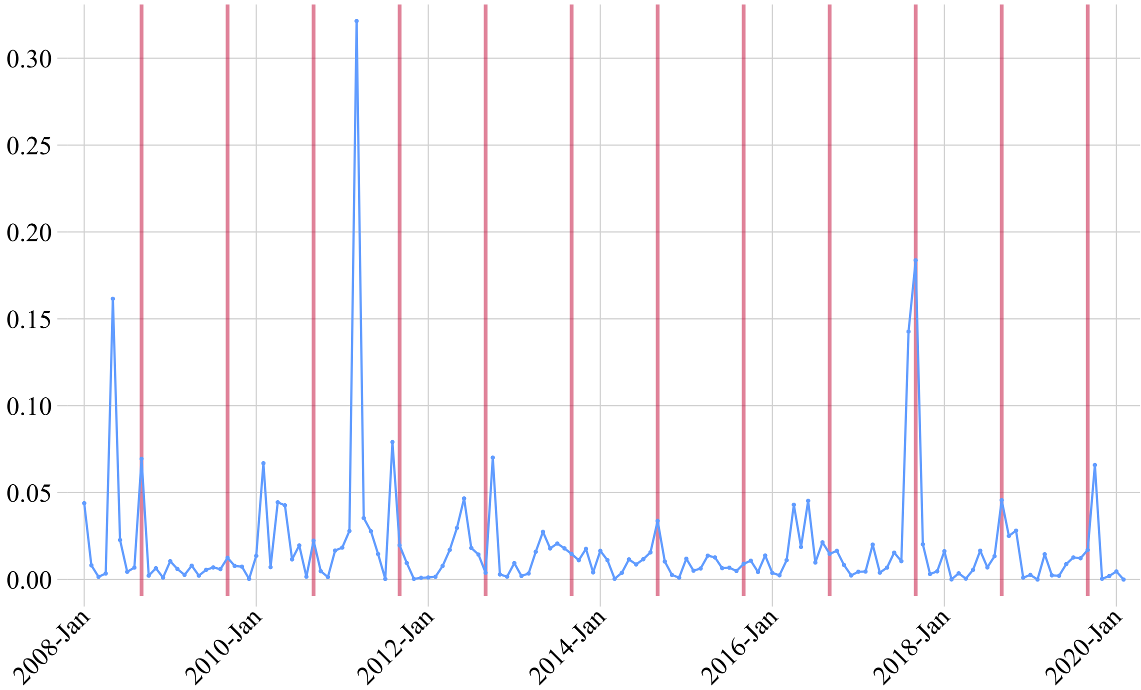
	N	Mean	Median	Std.Dev.
All Disaster Types				
Estimated Damage (USD Mn.)	129	5699.96	500.00	22521.43
Estimated Damage (% GDP)	129	7.17	0.69	26.57
Type = Climatological				
Estimated Damage (USD Mn.)	13	1136.52	500.00	1804.07
Estimated Damage (% GDP)	13	1.00	0.71	1.01
Type = Geophysical				
Estimated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

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

Figure 2 represent the evolution of estimated damage in percentage of GDP in aggregate caused by natural disasters. Hurricane and typhoon seasons are highlighted in red. Total damage to world GDP remains fairly stable since 2008. However damage caused during storm seasons appear to be increasing.

Figure 3 shows the geographical distribution of natural disasters events as defined by Equation 2. Countries marked in blue compose our permanent control group. Countries in red enter our treatment group in a staggered fashion. The shades of red indicates the severity (in percentage of GDP) of the damage caused by the event. 50% of natural disasters cause damage lower than 0.69 percent of GDP. Only eight of them caused damages equal to more than 4 percent of GDP.

Figure 2: Natural Disasters

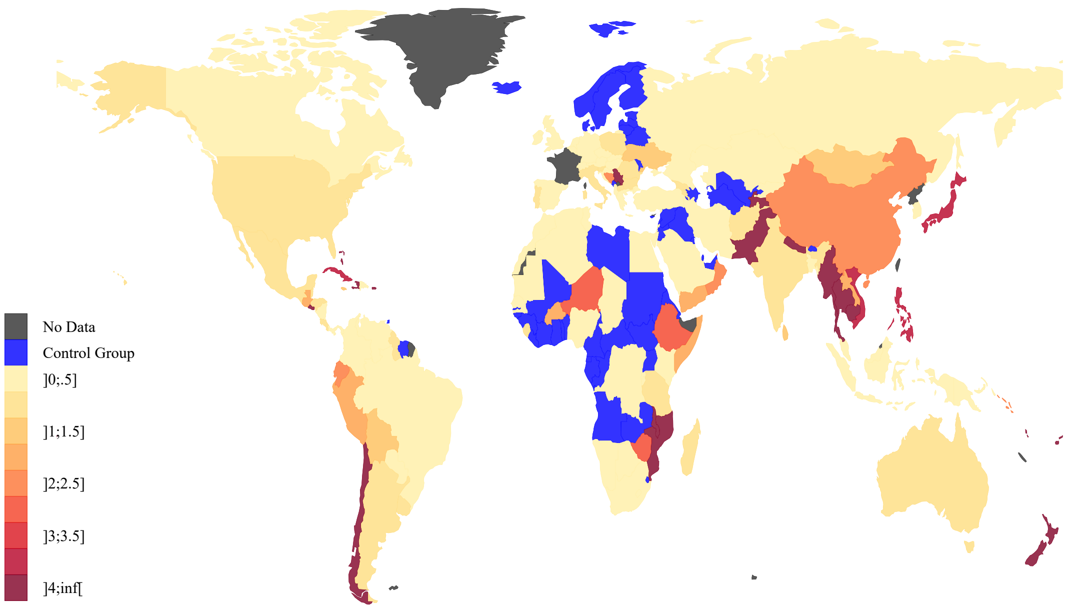


NOTE: These figure presents estimated damage in percentage of GDP caused by natural disasters. The source for the disaster data is EM-DAT. Authors' computations.

Estimation Sample

We keep observations for which we have both disaster and trade credit data. The final sample (see Table 3) consists of 14,692,164 observations (i.e. supplier-destination-month triads) over a hundred and twenty months from January 2010 to December 2019. We have 146,833 distinct supplier-destination linkages in 181 countries and 9,615 French suppliers. Of those supplier-destination dyads, 29,537 (37%) are never treated. The rest suffers from a natural disaster at some point during the sample period. On average about 2% of those dyads are treated each month. The control group used in the estimation is composed of both never treated and not yet treated observations.

Figure 3: Geographical Distribution of Natural Disasters Events



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

Table 3: Sample

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

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

2.2 Empirical Strategy

We want to estimate how natural disasters change the structure of the supplier's network of buyers. We look at various outcomes that characterise this network (e.g. the number of buyers in the affected country, the overall amount of exposure or the average exposure per buyer). We assume a simple data generating process such as:

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

Where Y is some variable describing the trade network outcome of supplier f in the destination country j at period t. The change of Y is determined by some time varying components common to certain groups of observations regardless of their treatment status. Those could be the business cycle in the destination country or firm-specific supply shocks. The first identifying assumption is that suppliers operating in affected and unaffected countries would have had the same outcome in the absence of a natural disaster. The second is that natural disasters are exogenous to trade in the short-run (at least within a 24 months window around the event).

We rely on a Differences-in-Differences strategy and exploit the fact that some countries are hit by natural disasters at different times or not at all. We use the de Chaisemartin and d'Haultfoeuille (2020) estimator. It accounts for the weighting issues generated by standard differences-in-differences estimator (see for instance Callaway and Sant'Anna (2019) and Goodman-Bacon (2018)). In particular, they show that the coefficients identified by the canonical two-way fixed effect (TWFE) model are a combination of the actual treatment effect and weights. In the case of a staggered design, the TWFE mechanically computes negative weights for some periods and groups. In some cases it can result in negative estimated coefficients when the treatment effects are in fact positive. This problem is more acute in the presence of treatment effect heterogeneity, either across groups or across periods.

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

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

Where

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

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

Each treatment effect $DID_{t,k}$ is estimated with OLS. The de Chaisemartin and d'Haultfoeuille (2020) Differences-in-Differences estimator absorbs permanent differences between destinations. To account for time varying shocks, we residualize the outcome variables over either region-sector-month or firm-month fixed effects. The former accounts for common shocks across supplier-destination pairs within regions-sectors-months. The identification comes comparing several suppliers operating in the same sector but exporting to different countries within the same region, where at least one will be affected by a disaster. The latter accounts for the suppliers shocks common to all their destinations. This specification limits the sample to supplier present in two or more destination. Here identification results from the supplier exporting to at least two different countries, one of which is hit by a disaster at some point. In the second case, identification. We cluster the standard errors at the region-sector level. It allows for auto-correlation of the error term within regional sectors. It also allows for correlation across buyers within those regional sectors.

Throughout the paper, we show the results of estimating DID_k to evaluate the time-varying impact of natural disasters on the international network of French suppliers. As a baseline, we estimate DID_k with the outcome variables $\tilde{Y}$ measured in level (amount in euros, number of buyers, etc.). This yields the average change ΔY in affected destination relative to unaffected destination. It does not require the omission of observations taking the value zero as opposed to using the log of those outcomes. We expect a higher frequency of zero flow to the affected destination in the aftermath of the disaster. Dropping those observations would bias $DID_{t,k}$ toward zero. We provide results robust to functional forms mis-specification in Section 3.2.

3 Results

We first present our main results in section 3.1 on the effect of natural disasters on the size of suppliers' network in affected countries. We then explore the effect on the shape and quality of the network in Section 3.2.

3.1 Main Results

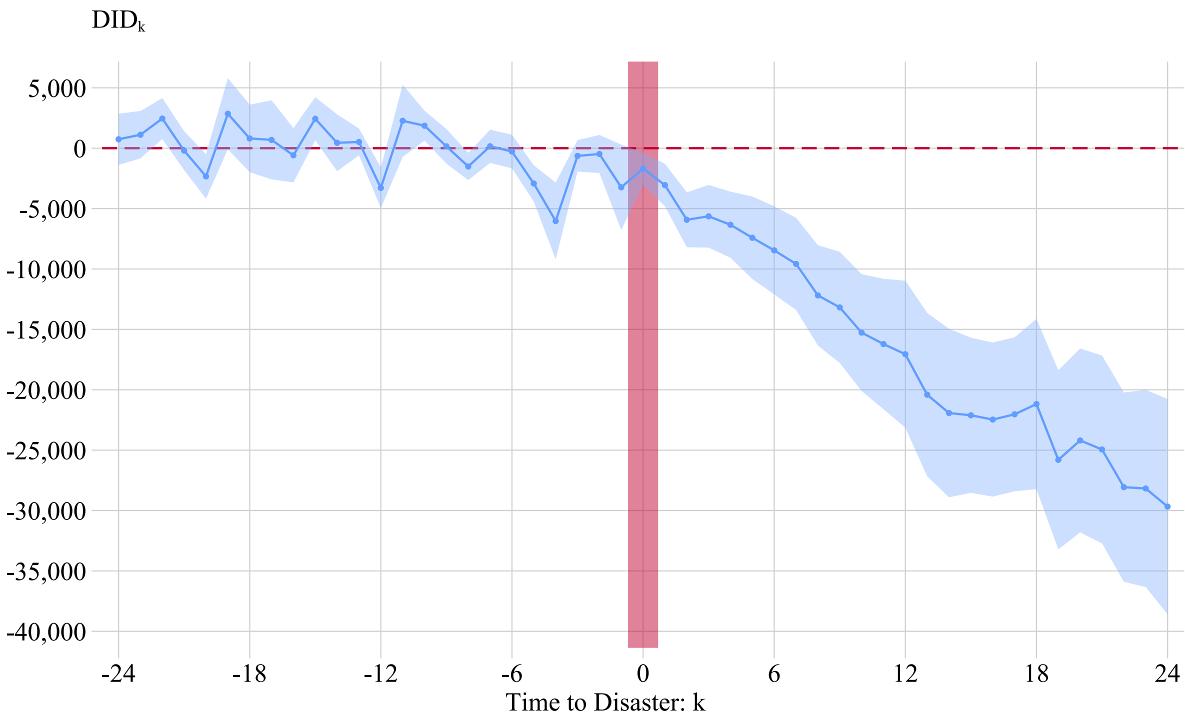
We first present our result on the effect of natural disaster on the use of trade credit by French suppliers selling in affected destinations. In Figure 4, we plot the time varying effect of a disaster on French suppliers' trade credit exposure to clients in affected countries. The outcome variable is the amount in euros of trade credit exposure for a given supplier in the affected country. After the disaster, exposure decreases by €17,000 after 12 months and €29,600 after 24 months. The average trade credit exposure is 256,150 (P50 = 10,000; SD =1,929,330). The total loss after 24 months represents a 6.66% (12 months) and a 11.59% (24 months) decrease in trade credit exposure to the affected destination relative to the sample mean.

The decline in trade is entirely explained by the "2^{nd} extensive margin"

We can decompose this effect in an extensive and intensive margin. The disaggregated nature of the underlying trade credit data allows us to compute both the "1^{st} extensive margin" i.e. the existence of a trade credit relationship in the destination country and the "2^{nd} extensive margin" i.e. the number of buyers using trade credit terms in the destination country. To measure the effect on the intensive margin, we compute the average trade exposure per trade credit buyer in the destination country. We provide details on the computations of those variables in Appendix B.

In Figure 5, we show that the impact is driven by the 2^{nd} extensive margin, i.e. the number of clients rather than the exposure per client. The effect increases from about from -0.11 buyers after 12 months to -0.18 buyers after 24 months and is robust to the inclusion of firm-time fixed effects and sector-region-time fixed effects (Figure 5a). The average number of buyers in the

Figure 4: Effect of Natural Disasters on Exposure



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

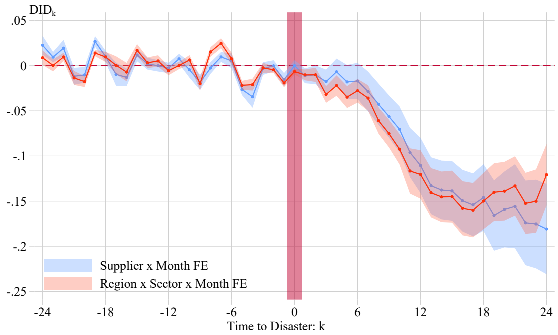
sample is 2.49 (P50 = 1; SD = 13.51). This represents a 7.22% decline in the number of buyers using trade credit 24 months after a disaster. Meanwhile, we find no effect on the probability of being present in an affected destination (Figure 5b). We also find no impact on the intensive margin (Figure 5c).

Persistence of the effect five years later

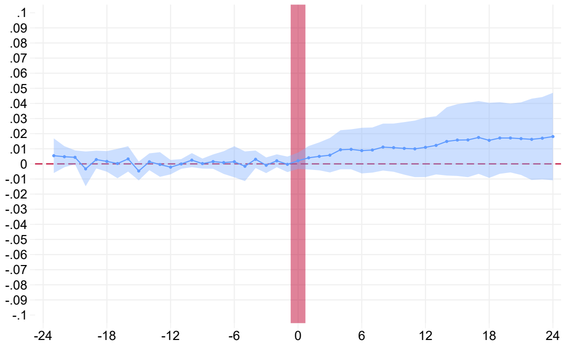
To assess the long run consequences of natural natural, we repeat the same estimation procedure as in Equation 4 and Figure 5a on a sample aggregated at the yearly level. We present those results in Figure 6. We find that the number of buyers in the affected country continues on declining until four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

Figure 5: Extensive and Intensive margin

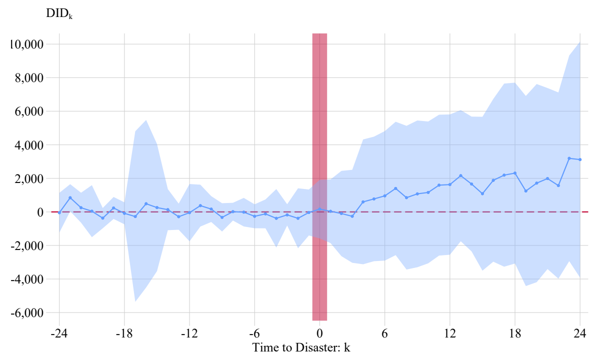
(a) Number of Buyers with Trade Credit



(b) 1st Extensive Margin



(c) Trade Credit / Number of buyers

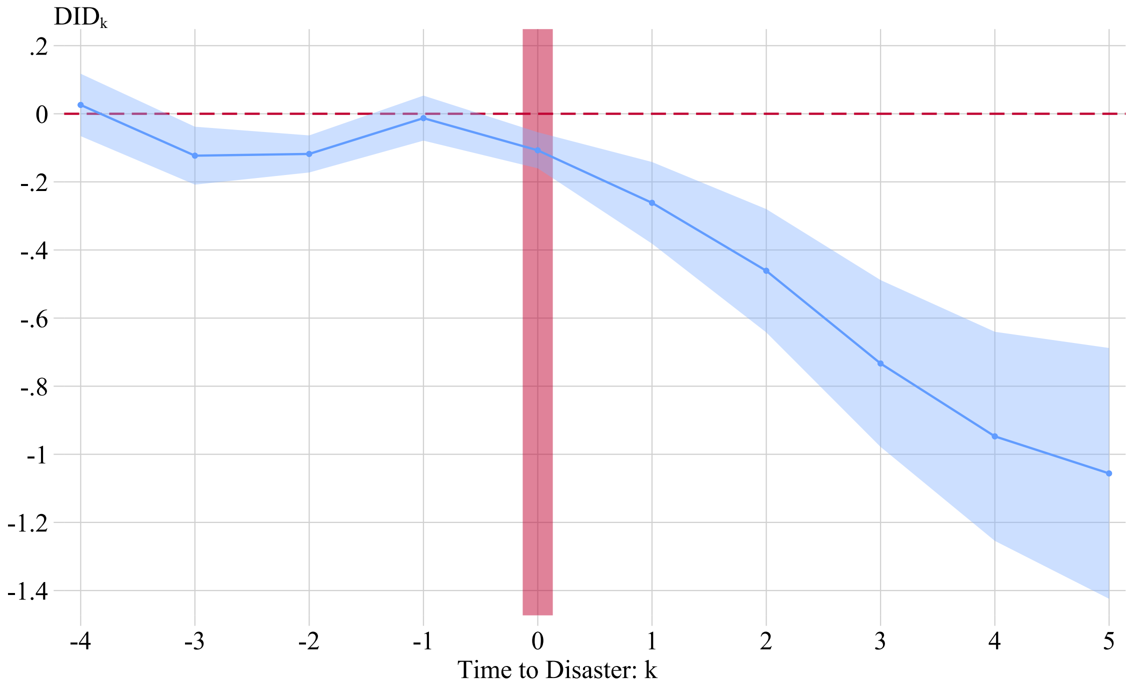


NOTE: These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 5. 99% error bands, computed with robust standard errors clustered at the region-sector level, are displayed as blue lines. Events are defined as natural disasters above the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

Trade and natural disasters

The decrease in the number of buyers using trade credit likely reflects a lower number of domestic firms sourcing from French suppliers. Indeed, according to previous work by Garcia-Marin et al. (2020) firms rarely switch away from trade credit. We investigate this by looking at the effect of natural disasters on the actual supplier level exports as measured in custom data. We keep the same specification as before. The sample contains firms that are present in both French customs and Coface data. As a consequence it only extends from 2010 to 2018. We first estimate the effect on the total value in euros exported by French suppliers to their destination.

Figure 6: Long run effect (yearly data)



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

We then repeat the exercise with the quantities (in kilograms), number of products (at the HS6 level in the 2007 nomenclature) and the unit values (euros per kilogram). We report the result in Figure 7. In panel 7a, we show that the value of the transactions toward the affected destinations decreases by about €11,300 in the two years following a disaster. This effect increases to about minus €18,900 after five years. In panel 7b, we see that the effect on quantities tracks closely the one on values. In fact, panel 7c shows that the effect on unit values while positive, is not statistically significant. Finally, panel 7d indicates that natural disasters leads to a lower number of exported products (-0.15) after five years. We also do not find evidence of an effect on the probability of exporting to a country struck by a natural disaster (not reported here).

We can make three observations from this last set of results. First, the overall pattern of results is similar whether we use the French custom or the Coface database. Natural disasters causes a permanent drop in the intensity of the trade linkages with the affected destination. Second, the effect on the number of products (Figure 7d) taken together with the results on the number of buyer-supplier relationships in Figure 5a underlines the importance of the within-country extensive margin in the adjustment to major shocks. Third, the losses measured in trade credit and in export sales are of a similar order of magnitude. After just two years, the level of traded goods has fallen by €11,300 (Figure 7a). This represents a 6.61% decline versus a 11.58% decline in trade credit. This indicates that a large negative shock not only impacts the size of the trusted network of buyers to whom the supplier will extend trade credit. It also impacts the cross-border movement of goods.

3.2 Effects on the distribution of buyers and suppliers

The effect is concentrated on suppliers with few buyers

To help disentangle between supplier side or buyer side explanations to explain the fall in the number of buyers, we estimate the effect of a natural disaster on the cumulative distribution of buyers per supplier-destination. If the effect is concentrated among suppliers with many buyers, it would suggest that suppliers with enough market power are able to change the terms of future transactions by requiring cash-in-advance. If it is concentrated among suppliers with fewer buyers it would reflect the propensity of large suppliers to support their buyers through trade credit provision in degraded environments.

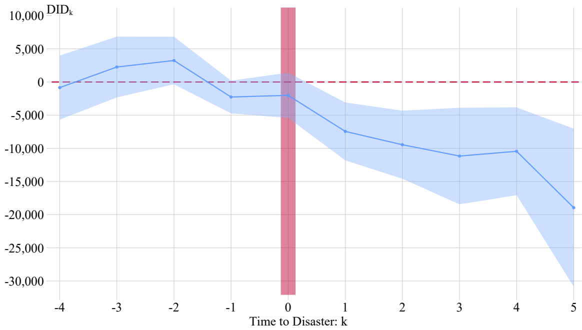
We estimate the same equation as in Equation 4 but we replace the outcome variable with a dummy equal to one for supplier-destinations with a number of buyers greater than x. We repeat this estimation for every possible value of x (from 0 to 50, the 99^{th} percentile) in increments of 1. This method allows to estimate the entire conditional distribution. Importantly, it does not require the outcome to have a smooth conditional density as in quantile regressions (Chernozhukov et al., 2013). [4]

Figure 8a plots the effect on the distribution along the values of the outcome variable, here

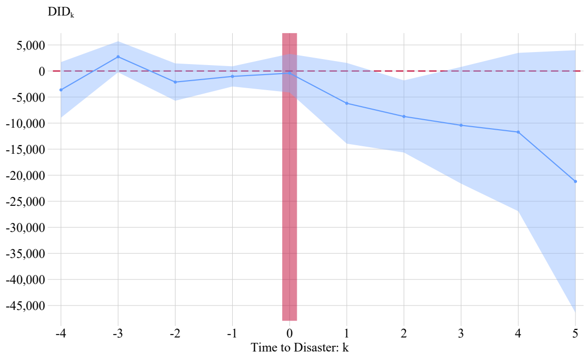
[4]See Aghion et al. (2019), Goodman-Bacon and Schmidt (2020) or Blanc (2020) for recent applications.

Figure 7: Long Run Effects of Natural Disasters on the Export of Goods

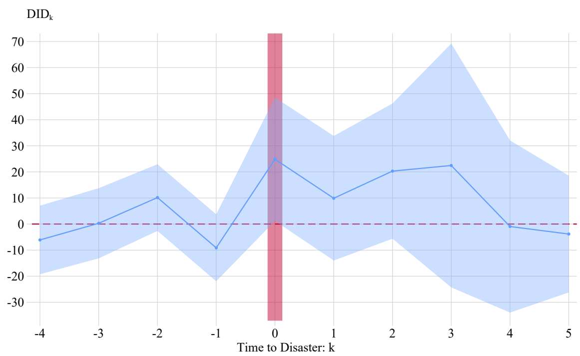
(a) Total Transaction Value (Euros)



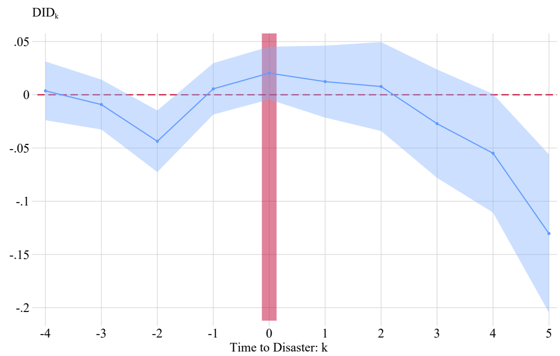
(b) Total Transaction Quantity (Kg)



(c) Unit Value (Euros/Kg)



(d) Number of Products (HS6)



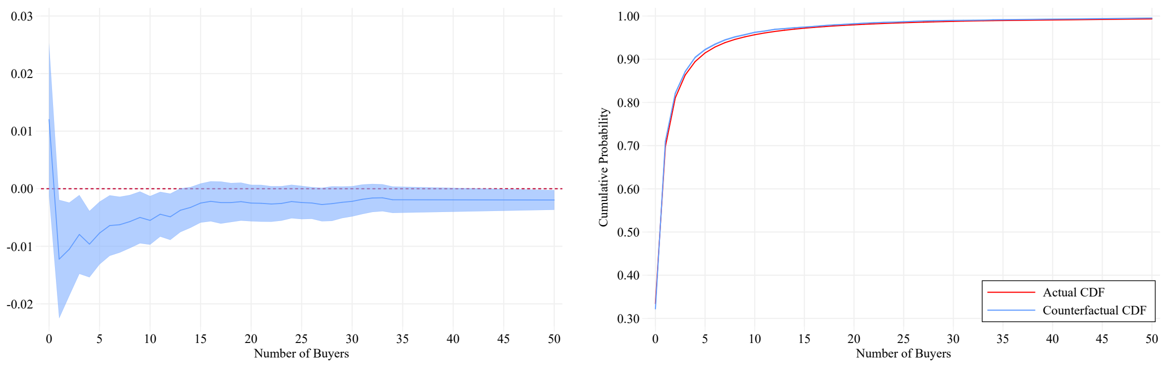
NOTE: These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 5. 99% error bands, computed with robust standard errors clustered at the region-sector level, are displayed as blue lines. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2010 and 2019, we consider only the largest one. In Panel 7a, the outcome variable is the total value in euros exported by french suppliers to their destination. In Panel 7b, the outcome variable is the quantity exported in kilograms. In Panel 7c, the outcome variable is the unit values (euros per kilogram) of the exports. In Panel 7d, the outcome variable is number of exported products in each destination defined at the HS6 level in the 2007 nomenclature. See Appendix B for the details on the computations of those variables.

the number of buyers. We see that the effect measured in our baseline specification is largely explained by a decrease in the probability of having just a few buyers per destination. The effect on the probability of having at least a single buyer is slightly positive (about one percentage point) but not statistically significant. A disaster decreases the probability of having more than two suppliers by 1.2 percentage points and more than five suppliers by about 0.8 percentage points. The higher in the distribution, the lower the effect is. This effect stabilize at about minus 0.1 percentage point between the 95^{th} and 99^{th} percentile of the distribution. We show in Figure 8b that it results in a shift of the cumulative distribution towards the left. In other words, it increases the skewness of the distribution of buyers per supplier-destination.

This confirms the solidarity hypothesis according to which suppliers with few buyers are likely to be smaller and therefore more financially constrained with lower flexibility to show solidarity with their buyers compared with larger suppliers.

Figure 8: 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. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue lines. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2013 and 2020, we consider only the largest one. The outcome variable is the number of buyers per supplier-destination. In Panel 8a, we plot the sequence of coefficients from estimating the baseline equation for every value of x. In Panel 8b, we plot the observed CDF in red and the estimated counterfactual CDF in blue. For details on distribution regressions see Chernozhukov et al. (2013).

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

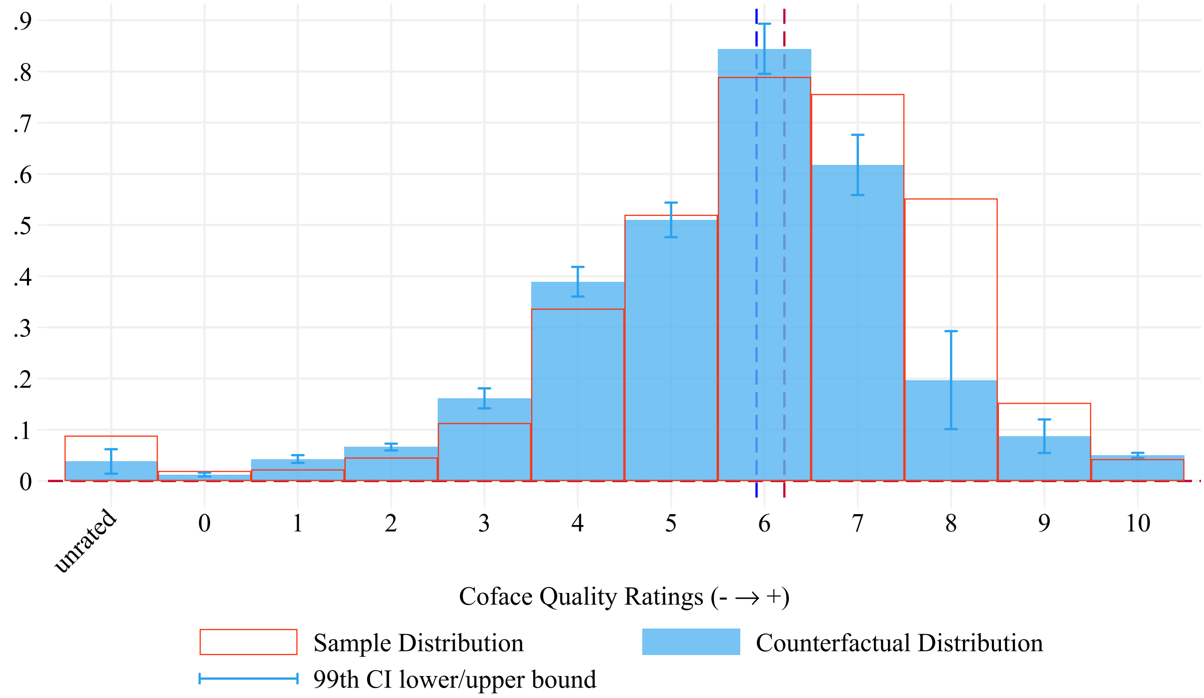
We now focus on the effects of disasters on the quality of the supplier's network of buyers in the destination country. We proxy quality with the Coface internal ratings of buyers. Ratings are based on a combination of fiscal data, experts opinions and external ratings. A rating of 0 is the lower possible. A rating of 10 indicates that the buyer's "performance solidity is undoubted" [5]. We note that both unrated and the "0" category are not as homogeneous as other rating categories. Unrated firms are made up of both new buyers that haven't been rated yet and buyers whose identity is withheld by the supplier as part of a somewhat rare special type of contract. Firms rated "0" are made up of firms that are either ceasing their activity for any

[5] Internal Coface documentation. A Coface rating of "0" is equivalent to a "D" rating by S&P, while a "10" corresponds to a rating between "AA-" and "AAA".

possible reasons or firms that are currently defaulting on their payments.

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

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

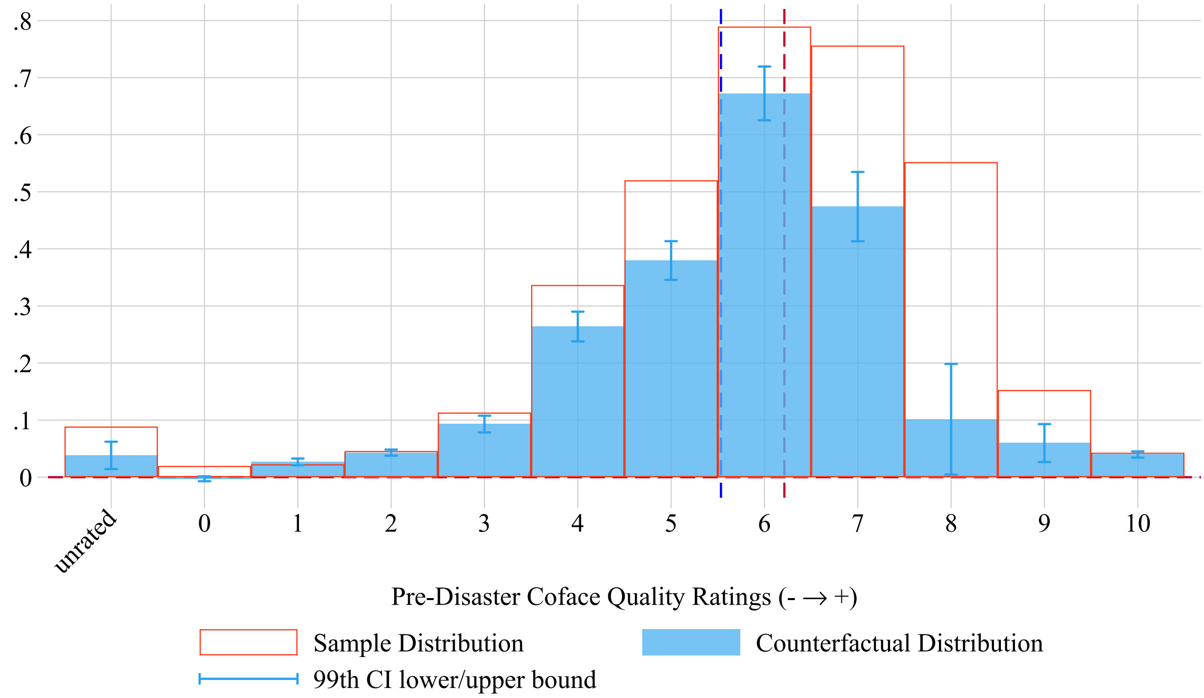


NOTE: These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 5. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue brackets. Events are defined as natural disasters above the median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

We find that in the aftermath of a disaster the distribution of ratings has shifted toward the left, i.e. it has worsened. In particular, there is a much lower number of suppliers in ratings 7 to 9. 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.

In Figure 10, we present the same analysis as in Figure 9, but this time we freeze each buyer's rating at the time of the disaster and then count each month the number of buyers still active from each prior category. We compute this number doing: $T^{r}_{j,f,t} = \sum \mathbf{1}(EXPO_{j,b,f,t} > 0 \cup R_{b,k} = r)$ with k the month of the event. Contrary to what we could have imagined, we see that the drop affects more buyers which were highly-rated at the time of the event (ratings from 7 to 9 with 8 being the most impacted). The most fragile firms are not the most affected ones. This result, in combination with the heterogeneity we observe on the supplier side in Figure 8, can be understood when taking into account assortivity mechanisms as described by Bernard et al. (2018) and Blum et al. (2010). They highlight how negative assortivity characterizes supplier-buyer pairs in trade. Large supplier will tend to match with smaller buyers while large buyers will match with smaller suppliers. If we take the number of buyers as a proxy for the supplier size and the rating for the buyer size, then it appears that the drop in the number of partners is concentrated on small suppliers – large buyer pairs. From Garcia-Appendini and Montoriol-Garriga (2013) we know that small suppliers – with higher financial constraint – will be less inclined to support their buyers in degraded environment. Thus, higher-rated and more financially sound buyers have to absorb the shock alone without further help from their supplier. To survive, those buyers will likely restrict their input sourcing toward suppliers with lower trade costs, switching away from French suppliers.

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



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

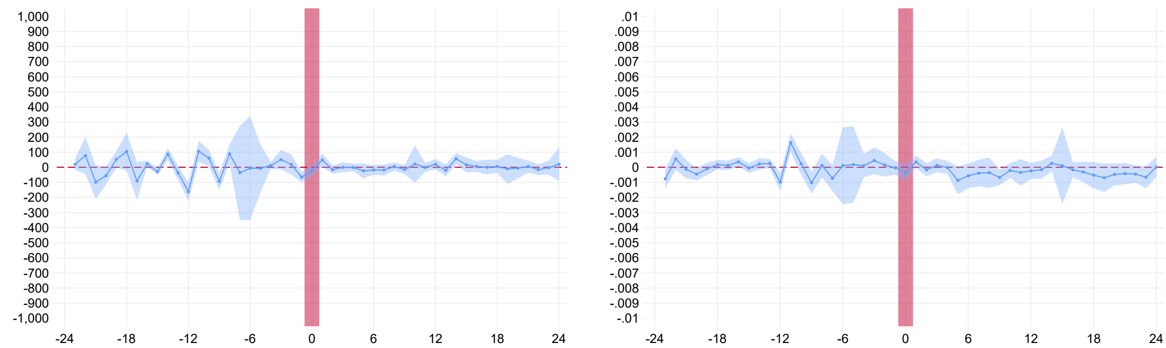
4 Robustness

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

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

Figure 11: 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. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue lines. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2008 and 2019, we consider only the largest one. In Panel 11a, the outcome variable is the amount of trade credit that buyers in the affected destination default on. In Panel 11b, the outcome variable is the number of defaults. See Appendix B for the details on the computations of those variables.

4.2 The effect is not explained by credit insurance rationing

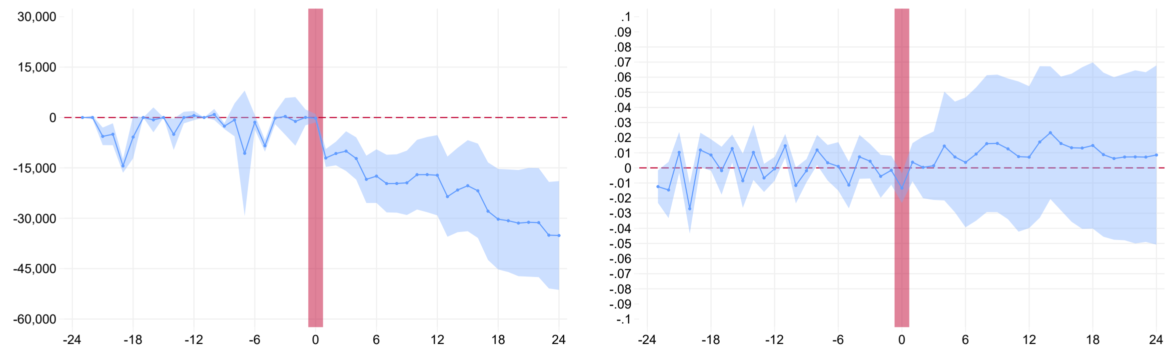
The decline in trade credit to the affected destination could be caused by trade credit insurance rationing. The credit insurer could decide to lower the amount of issued insurance around the time of a disaster. To rule out this mechanism, we use the information on the amount of insurance requested by the supplier and compare it to the amount effectively granted by the insurer Coface. In Figure 12a, 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 12b. We find the effect to be small (lower than 1 percentage point change) and not statistically significant. This indicates that the effect reflects a change in demand by the supplier rather than a change in supply by the insurer.

4.3 Alternative Estimator: two-way fixed effect

We use a fully dynamic saturated two-way fixed effect estimator as in Borusyak and Jaravel (2017). It accounts for both permanent differences across suppliers and common shocks be-

Figure 12: Supplier vs. Insurer Effect

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



NOTE: These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 5. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue lines. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2013 and 2020, we consider only the largest one. The outcome variables are: in Panel **??** the requested amount of trade credit guarantee requested by the supplier and in Panel **??** the ratio of obtained trade credit guarantee over requested. See Appendix B for the details on the computations of all LHS variables.

tween suppliers. We test how natural disasters change the structure of the supplier's network of buyers. Formally, we estimate the following equation:

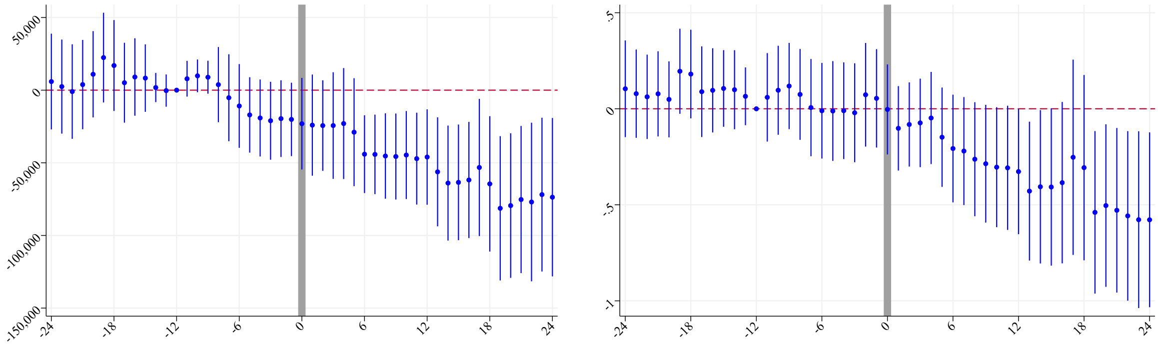
$$Y_{f,j,t} = \sum_k \beta_k + \gamma_{j,f} + \gamma_{t,r,n} + \upsilon_{f,j,t} \tag{6}$$

where f indexes the suppliers, j the countries, n the 2-digit industry, r the region and t the month. $E_{j,t}$ indicates that a natural disaster occurred in country j at time t. k indexes the months relative to the date of the event E. Y is the supplier's network in country j: Nb of buyers, exposure per buyers, total exposure, etc. $\gamma_{j,f}$ and $\gamma_{t,r,n}$ are respectively firm-destination and month-region-industry(2-digit) fixed effects. We use two-way clustering of the standard errors: country-time and country-supplier

We show the estimated coefficient β_k in Figure 13. We find a pattern of results that closely follows our key result in Figure 5c.

Figure 13: Effect of Natural Disasters on Exposure

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

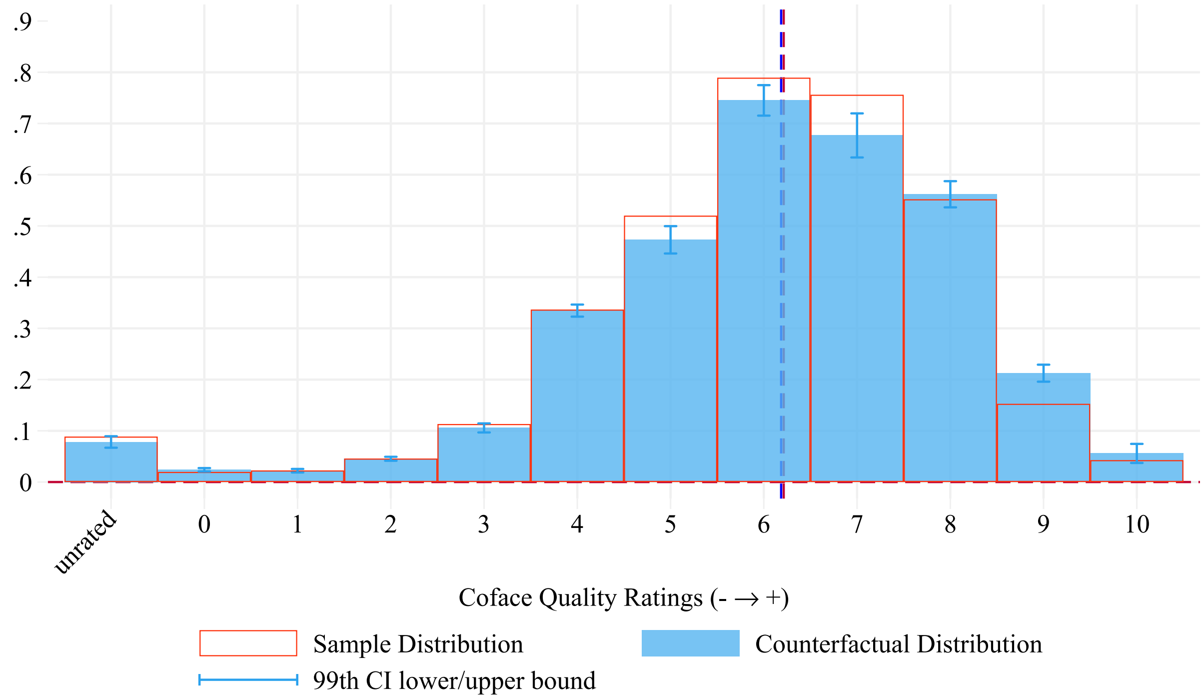


NOTE: These figures present estimates of the coefficient β_k associated with natural disaster events from estimating this equation: $Y_{f,j,t} = \sum_k \beta_k E_{j,t} + \gamma_{j,f} + \gamma_{t,r,n} + \upsilon_{f,j,t}$. 99% error bands, computed with robust standard errors two-way clustered at the country-period and country-supplier level, are displayed as blue lines. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2013 and 2020, we consider only the largest one. The outcome variable is the amount in euros of trade credit insurance for a given supplier in the affected country in Panel 5 and the share of that country in the total exposure of each supplier.

4.4 Absence of anticipatory effects per ratings category

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

Figure 14: Effect of Natural Disasters on Buyer Quality after 2 Years



NOTE: These figures present estimates of the coefficient $DID_{k=1,k=2}$ associated with natural disaster events from estimating Equation 5. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue brackets. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2008 and 2019, we consider only the largest one. The outcome variable is the number of buyers each supplier has in each rating category. We plot the sample distribution of ratings in red and its counterfactual distribution in blue.

5 Conclusion

Summary

In this paper, we show evidence that natural disasters cause large and permanent disruptions to international buyer-supplier relationships. They do so mostly through the extensive margin by reducing the number of buyers using trade credit rather than the amount of trade credit exposure per buyers. The reduction in the size of the supplier's network of buyers is compounded by a lower level of export sales. We find that this decreased exposure is caused by a lower demand for trade credit by the supplier rather than a decrease in the amount of insurance granted by the credit insurer. We do not find any evidence of an increase in the number of defaults on their trade credit by clients. We further rule out market power as a channel by highlighting that the negative effect of natural disasters is concentrated among suppliers with few buyers rather than suppliers with many buyers. Instead, we show that high quality buyers, which are typically matched with relatively smaller and more financially constrained suppliers, are the ones with the highest exit rate. While those high-quality buyers leave the French supplier's network, they do not appear to do so after a default. This leaves open the possibility that they now source from suppliers with a lower trade cost, including domestic suppliers.

Interpretation

Our results emphasize the importance of the buyer margin in the adjustment to trade shocks. It matches well with the empirical regularity noted by Bernard and Moxnes (2018). Those results can be easily interpreted within a framework of a model of trade with exporter and importer heterogeneity such as Bernard and Moxnes (2018). Both suppliers and exporters are heterogeneous in terms of productivity. They face a sunk cost in order to meet and a repeated iceberg cost each period. Natural disasters affect both the distribution of productivity in the destination country and the buyer-supplier trade cost. It implies a lower overall number of buyers. In terms of quality of those remaining buyers, the implications 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 fall in productivity among the potential buyers, all else equal, would lead to a lower quality of remaining buyers. The observed decline in quality that we observe after a disaster indicates that this second mechanism prevails.

Another key result that we document is the persistence of the decline. A temporary idiosyncratic shock in the destination country, like a natural disaster, cannot alone explain this persistence. We suggest that the natural disaster forces buyers to search for new suppliers where the trade cost is lower than for importing from France. This mechanism is reminiscent of the "forced experimentation" highlighted by (Porter, 1991) with regards to environmental regulation. Given the amount of information frictions in international trade, many buyers might find a supplier that is good enough and it is not longer optimal for them to re-establish a relationship with a French supplier. This would lead to permanent trade diversion as foreign buyers find new suppliers. This would also be consistent with a model of importer heterogeneity as in Antras et al. (2017). They highlight that the choices to source from one location or another are not independent. This stands in contrast with the choice to export to more destinations in models of trade with exporter heterogeneity as in Melitz (2003). Finally, the absence of a 1^{st} extensive margin adjustment can be explained with the higher option value associated with the decision to exit a country versus the option value of ending a single relationship under uncertainty about post-disaster recovery. It is public knowledge for a supplier that a country has been hit by a disaster. However, the supplier would be aware that the impact is likely very heterogeneous across sectors and areas but unaware of the distribution of the impact. This corresponds to an increase in the dispersion of the future pay-offs associated with continuous exporting to the affected country i.e. a risk shock or uncertainty shock. For a given level of uncertainty, the size of the sunk cost is the key determinant in the decision to "wait and see" (Dixit et al., 1994).

References

Aghion, P., A. Bergeaud, T. Gigout, M. Lequien, and M. Melitz (2019). Exporting ideas: Knowledge flows from expanding trade in goods. *manuscript, Harvard University*.

Antras, P., T. C. Fort, and F. Tintelnot (2017). The margins of global sourcing: Theory and evidence from us firms. *American Economic Review 107*(9), 2514–64.

Barrot, J.-N. and J. Sauvagnat (2016). Input specificity and the propagation of idiosyncratic shocks in production networks. *The Quarterly Journal of Economics 131*(3), 1543–1592.

Bernard, A. B. and A. Moxnes (2018). Networks and trade. *Annual Review of Economics 10*, 65–85.

Bernard, A. B., A. Moxnes, and K. H. Ulltveit-Moe (2018). Two-sided heterogeneity and trade. *Review of Economics and Statistics 100*(3), 424–439.

Blanc, G. (2020). Modernization before industrialization: cultural roots of the demographic transition in france. *Available at SSRN 3702670*.

Blum, B. S., S. Claro, and I. Horstmann (2010). Facts and figures on intermediated trade. *American Economic Review 100*(2), 419–23.

Boehm, C. E., A. Flaaen, and N. Pandalai-Nayar (2019). Input linkages and the transmission of shocks: firm-level evidence from the 2011 tōhoku earthquake. *Review of Economics and Statistics 101*(1), 60–75.

Borusyak, K. and X. Jaravel (2017). Revisiting event study designs. *Available at SSRN 2826228*.

Bricongne, J.-C., L. Fontagné, G. Gaulier, D. Taglioni, and V. Vicard (2012). Firms and the global crisis: French exports in the turmoil. *Journal of international Economics 87*(1), 134–146.

Callaway, B. and P. H. Sant'Anna (2019). Difference-in-differences with multiple time periods. *Available at SSRN 3148250*.

Carvalho, V. M., M. Nirei, Y. Saito, and A. Tahbaz-Salehi (2016). Supply chain disruptions: Evidence from the great east japan earthquake. *Columbia Business School Research Paper* (17-5).

Chernozhukov, V., I. Fernández-Val, and B. Melly (2013). Inference on counterfactual distributions. *Econometrica 81*(6), 2205–2268.

de Chaisemartin, C. and X. d'Haultfoeuille (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review 110*(9), 2964–96.

Dixit, R. K., A. K. Dixit, and R. S. Pindyck (1994). *Investment under uncertainty*. Princeton university press.

El Hadri, H., D. Mirza, and I. Rabaud (2019). Natural disasters and countries' exports: New insights from a new (and an old) database. *The World Economy 42*(9), 2668–2683.

Fratzscher, M., C. Grosse-Steffen, and M. Rieth (2020). Inflation targeting as a shock absorber. *Journal of International Economics 123*, 103308.

Garcia-Appendini, E. and J. Montoriol-Garriga (2013). Firms as liquidity providers: Evidence from the 2007–2008 financial crisis. *Journal of financial economics 109*(1), 272–291.

Garcia-Appendini, E. and J. Montoriol-Garriga (2020). Trade credit use as firms approach default. *Journal of Money, Credit and Banking 52*(5), 1199–1229.

Garcia-Marin, A., S. Justel, and T. Schmidt-Eisenlohr (2020). Trade Credit, Markups, and Relationships. *FRB International Finance Discussion Paper* (1303).

Goodman-Bacon, A. (2018). Difference-in-differences with variation in treatment timing. Technical report, National Bureau of Economic Research.

Goodman-Bacon, A. and L. Schmidt (2020). Federalizing benefits: The introduction of supplemental security income and the size of the safety net. *Journal of Public Economics 185*, 104174.

Kashiwagi, Y., Y. Todo, and P. Matous (2018). Propagation of shocks by natural disasters through global supply chains. Technical report, RIETI Discussion Paper.

Larcom, S., F. Rauch, and T. Willems (2017). The benefits of forced experimentation: striking evidence from the london underground network. *The Quarterly Journal of Economics 132*(4), 2019–2055.

Lenoir, C., J. Martin, and I. Mejean (2019). Search frictions in international good markets.

Malgouyres, C., T. Mayer, and C. Mazet-Sonilhac (2019). Technology-induced Trade Shocks? Evidence from Broadband Expansion in France. CEPR Discussion Papers 13847, C.E.P.R. Discussion Papers.

Martin, J., I. Mejean, and M. Parenti (2020). Relationship stickiness, international trade and economic uncertainty.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *econometrica 71*(6), 1695–1725.

Muûls, M. (2015). Exporters, importers and credit constraints. *Journal of International Economics 95*(2), 333–343.

Porter, M. (1991). America's green strategy, scientific american, april. p. 96.

APPENDIX

A 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

B Variable Description

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

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

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

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

- Total Number of buyers in each buyer country for each supplier.

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

- Total Number of buyers in each destination country for each supplier for a given rating $R = r$.

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

- 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.

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

1

- "Notification of Overdue Account" Total Amount: Total amount of defaults on trade credit in each buyer country for each supplier

$$DEF_{j,f,t} = \sum_B DEF_{j,b,f,t}$$

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

$$PDEF_{j,f,t} = \sum_B PDEF_{j,b,f,t}$$

- NOA amount INSOLVENCY: Total amount of defaults due to buyers' insolvencies in each buyer country for each supplier

$$INS_{j,f,t} = \sum_B INS_{j,b,f,t}$$

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 DEFAULT & NOA nb INSOLVENCY : same as amount but with count of defaulters

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

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

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

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

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

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

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